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# **Domestic Demand and Network Management in a User-Inclusive Electrical Load Modelling Framework**

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*Doctor of Philosophy*

THE UNIVERSITY OF EDINBURGH

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# Lay Summary

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The increasing interest in the implementation of various power demand transformations, such as demand side management (DSM) and voltage control and the encouraging results of the initial studies, have highlighted the need for a better understanding of the power demand of low voltage (LV) residential networks. Furthermore, it is expected that future alteration of the residential appliance mixture, because of the advances in technology, will have an impact on the shape and behaviour of residential load.

This thesis presents a study of the impact of current and future household load on the power demand curve and the network operation. In order to achieve this, a bottom-up load modelling tool was developed to create LV detailed demand profiles that include not only the active and reactive power demand, but their electrical characteristics as well. The methodology takes into account the user activity and behaviour and an appliance database which corresponds to the UK residential appliance mixture in order to calculate accurately the power demand of UK residential sector. The main advantages of this approach are the flexibility in altering the type and number of the appliances that populate a household and how easily it can be adapted to a different population, location and climate.

The usefulness of the developed tool is presented while investigating the impact of scenarios that simulate future load replacement and the network behaviour under certain methods of demand control, implementation of DSM and control of voltage on the secondary of the LV transformer.

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# Abstract

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Interest has been growing in the interaction of various power demand transformations, such as demand side management (DSM) and voltage control, with the power demand. Initial studies have highlighted the need for a better understanding of the power demand of low voltage (LV) residential networks. Furthermore, it is expected that future alteration of the residential appliance mixture, because of the advances in technology, will have an impact on both the demand curve as well as the electrical characteristics.

This thesis presents a study of the impact of current and future household load on the power demand curve and the network operation. In order to achieve this, a bottom-up load modelling tool was developed to create LV detailed demand profiles that include not only the active and reactive power demand, but their electrical characteristics as well. The methodology uses a Markov chain Monte Carlo approach to generate residential LV demand profiles taking into account the user activity and behaviour to represent UK population. An appliance database has also been created which corresponds to the UK residential appliance mixture in order to calculate more accurately the power demand. The main advantages of the approach presented here are the flexibility in altering the type and number of the appliances that populate a household and how easily it can be adapted to a different population, location and climate.

The tool is used to investigate the impact of scenarios that simulate future load replacement and the network behaviour under certain methods of demand control, implementation of DSM and control of voltage on the secondary of the LV transformer. The algorithm that was developed to apply the DSM actions on the power demand focused on the management of individual loads. The drivers used in this approach were the financial and environmental benefit of customers and the increase in the quality of the network operation.

The control of the voltage as a method for power reduction takes into account the voltage dependence of the demand. The primary target is to quantify the benefits of this strategy either in combination with DSM for higher power reduction during the peak hours or on the current network as a quicker, easier and less expensive alternative to DSM. The study shows that there is a significant power reduction in both cases which is dependent on the time of day and not constant as expected from the literature. The results show that there are significant differences between current and future load demand characteristics that would be very difficult to acquire without the modelling technique presented. The alternative solution would require extensive local load and network modifications and a long period of expensive tests and measurements in the field.

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# Declaration

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I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

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**George Tsagarakis**

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## Acronyms and abbreviations

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a-PFC	active power factor correction
BRE	Building Research Establishment
CC	constant current
CE	consumer electronics
CFL	compact fluorescent lamp
CP	constant power
CREST	Centre for Renewable Energy Systems Technology
CRT	cathode ray tube
CSR	capacitor start - capacitor run
CT	constant torque
CV	constant voltage
CVR	conservation voltage reduction
CZ	constant impedance
DECC	Department of Energy and Climate Change
DESIMAX	Multi-scale Modelling to Maximise Demand Side Management
DG	distributed generation
DNO	Distribution network operator
DR	demand response
DSM	demand side management
DVD	digital versatile disc
EE	Energy Efficiency
EPRI	Electric Power Research Institute
EV	electric vehicle
EVER	Electric Vehicles and Renewable Energy
GEV	Generalised extreme value
GHG	greenhouse gas
GIL	general incandescent lamp
HH	household
HID	high intensity discharge
HIL	halogen incandescent lamp
HU	highly-urban
ICT	information and communication technology
LCD	liquid-crystal display
LED	light-emitting diode

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LFL	linear fluorescent lamp
LV	low voltage
MCMC	Monte Carlo - Markov chain
MFD	multifunction device
MV	medium voltage
no-PFC	without power factor correction
OLTC	on load tap changing transformer
p-PFC	passive power factor correction
PC	personal computer
pdf	probability distribution function
PE a-PFC	power electronics loads with a-PFC
PE no-PFC	power electronics loads with no PFC
PE p-PFC	power electronics loads with p-PFC
PFC	power factor correction
PSU	power supplies unit
pu	per unit
QT	quadratic torque
RER	Renewable Energy Resource
RMS	root mean square
RSIR	resistor start - inductor run
SR	Spinning Reserve
SMPS	switch mode power supply
SPIM	single-phase induction motor
TIL	current loading of transformer
TOU	Time of Use
TUS	Time Use Survey
TV	television
UKERC	UK Energy Research Center
VAR	voltage-ampere reactive
VCR	videocassette recorder
ZIP	polynomial load model

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# Nomenclature

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$a$	appliance
$A_{ij}$	discrete probability functions of appliance use
$c_{comb}$	combined cost
$c_{em}$	average cost of the GHG emissions
$c_i$	price in £/MWh
$c_{wi}$	weighted value of the price
$cyc_{wt}$	the time period of the shifted wet load cycle
$D$	duty cycle
$em_i$	GHG emissions in tonnes of CO <sub>2</sub> eq./MWh
$em_{wi}$	weighted value of GHG emissions
$E_{old}/E_{new}$	daily energy before and after DSM
$f$	supply system frequency
$h$	household
$I_p$	constant current component of active power polynomial/ZIP model
$I_q$	constant current component of reactive power polynomial/ZIP model
$i, j$	user activity states
$J$	total number of activity states
$k$	shape factor for Generalised Extreme Value distribution
$m$	number of the occupants in household
$n_{ij}$	number of transitions from state $i$ to state $j$
$n_{swt}$	number of shifted cycles
$n_p$	coefficient of active power exponential load model
$n_q$	coefficient of reactive power exponential load model
$O_a$	device ownership
$P$	active power demand
$P_0$	nominal/rated active power demand
$P_a$	power demand profile for appliance
$P_{hh}$	household active power demand
$p_{ij}$	transition probability from state $i$ to state $j$
$p_{IC}$	probability of initial conditions
$P_p$	constant power component of active power polynomial/ZIP model
$P_q$	constant power component of reactive power polynomial/ZIP model
$p_{sharing}$	device sharing probability
$PF_{1a}$	displacement power factor of appliances

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$Q$	reactive power demand
$Q_0$	nominal/rated reactive power demand
$Q_{1,hh}$	household fundamental reactive power demand
$r$	randomly generated uniform number
$RMSE$	root-mean-square error
$R_{ph}$	line resistance per phase
$t$	time
$T$	temperature
$t_{disc}$	disconnection time
$t_{rec}$	reconnection time
$T_{i,a}$	probabilistic function of use of electrical appliance
$T_{peak}$	the period(s) of peak demand
$U$	user activity profile
$U_i$	user activity state
$V$	rms supply voltage
$V_0$	nominal/rated rms supply voltage
$V_{pu}$	voltage per unit
$X_{ph}$	line reactance per phase
$x,y$	weighting factor
$Z_p$	constant impedance component of active power polynomial/ZIP model
$Z_q$	constant impedance component of reactive power polynomial/ZIP model
$\lambda$	shape factor for Inverse Gaussian distribution
$\mu$	mean value
$\sigma$	scale parameter for GEV and Log-Logistic distribution
$\alpha$	scale parameter for GEV and Log-Logistic distribution
$\Omega$	SI derived unit of electrical resistance (Ohm)

# Introduction

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### 1.1 The gaps in existing perception of power systems

In recent years, there have been many studies on reducing power consumption while improving the quality of service and maintaining customers' comfort simultaneously. The electricity network and the whole system around it has been evolved and will continue to evolve in order to cover the increasing need for power. This will result in the expansion of the physical electricity network by the introduction of new technologies or the increase of the penetration of already participating ones. This highlights the need of changing the existing perception of the operation of power systems and considering the individual sectors that consist the wider energy system.

Previously, the energy system was being examined as a whole, including all the involved sectors, such as suppliers, distribution network operators (DNOs), policy makers and customers. The future enhancement of the network and the introduction of smart grids will lead to a more local study and management of the network needs to allow for better assessment and addressing of the issues that will arise. There are a lot of issues that researchers and, finally, system operators need to deal with. The penetration of distributed generation (DG) is expected to affect the energy balance and proper management is required to optimise the network performance. The network performance will also be affected by the increase in use of electronic devices and thus the harmonic distortion, which it still has to be investigated.

Another issue is the increase in energy consumption and especially in residential sector. According to [1], the residential sector is responsible for the majority of the annual UK energy consumption, which was approximately 50% in 2013. The introduction of modern technologies has resulted in more sophisticated and energy efficient domestic appliances which have started to replace the older appliances and will likely dominate in future households. Although, the operation of these appliances acts to mitigate the energy consumption, they simultaneously affect the power quality of the network which supplies them. Furthermore, no matter how "smart" and efficient the appliances can get, the factor that will always affects the most the energy consumption is the customers' behaviour. The intermittent use of residential loads and the randomness of switching on events has always been an obstacle in the precise load profiling and modelling.

Demand-side management (DSM) is part of a wider group of strategies that form the concept of smart grids and considers the users' needs in the decision making process. Although there has been some analysis on the functionality of smart grids, there is a variety of areas, which need to be studied further and one of them is the accurate representation of the load. The majority of existing studies use obsolete load models that are over two decades old [2] or use simplified load profiles which avoid any consideration of the electrical characteristics of the loads. The assessment of such an effect is a difficult task, especially without detailed load profiles of the individual operating appliances. This highlights the need for the development of accurate datasets of detailed load models that will update the existing load model library and will contribute to more accurate power flow studies which take into account the electrical characteristics of the individual appliances.

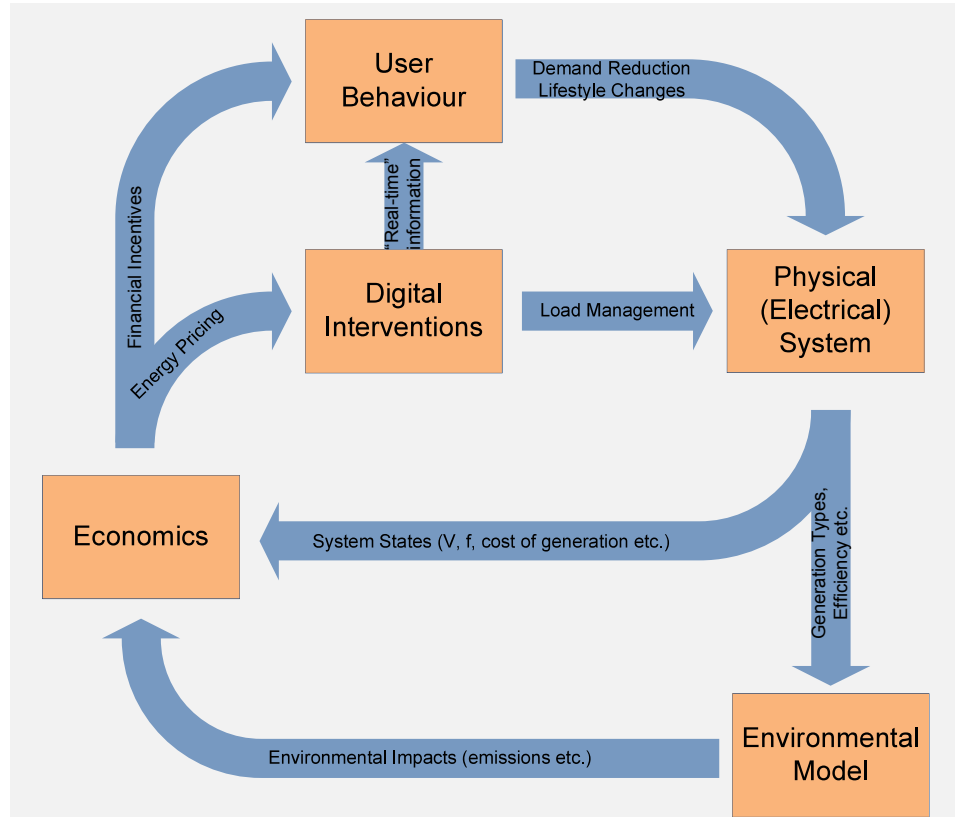
A modelling framework which takes into account the behaviour of the end-user would allow for detailed representation of the residential load. This tool can be the beginning and the base of further work by the research community in the first stage for more precise power system studies and better strategy planning. However, in long term, it could affect network operators in the decision making process and policy makers that are involved in the real-life energy system. These actions can be beneficial to more stakeholders since it could give a better, time-dependant picture of the required electrical power to suppliers and DNOs. And finally, all this interaction will affect customers financially and environmentally by improving their energy habits and minimising the deterioration of their comfort.

## 1.2 DESIMAX project

The research presented in this thesis is a part of a wider scale, multi-sector project, "Multiscale modelling to maximise Demand-side management" (in short, DESIMAX), which was funded by the U.K. Engineering and Physical Sciences Research Council under Grant EP/I000496/1 [3]. This project focused on the development of the whole-systems approach that is required for the full implementation of DSM within the overall energy supply system (from generation to transmission, distribution and utilization). A potential employment of DSM and spread of smart grids will cause changes not only within one part of the system, but across the overall electricity supply system affecting its performance and the sub-systems that are attached to it.

Figure 1.1 presents the modeling framework, including individual elements and their links and interactions. It has been divided into 5 distinctive but correlated topical entities (connected with communication infrastructure), represented by the electrical system, the digital interventions, the user behavior, the economic and the environmental models. All these individual sub-systems should be studied and modelled in order to achieve an end-to-end approach where the proposed digital framework will be able to link various stakeholders, helping them to express

their genuine interest in DSM and then identify, initiate and execute optimal measures and actions [4].



**Figure 1.1:** Demand-side Management modelling framework and information flow [4].

To emphasize the interactions between the key elements of the overall energy system, the project work was divided into four distinctive research themes: multi-scale dynamic modeling, digital interventions, economic analysis and open information fabric. The work of this thesis is included in the first of these themes.

### 1.3 Research objectives and scope

The research presented in this PhD thesis can be divided into two main objectives. The first is the development of a bottom-up load modelling tool capable of creating detailed low-voltage (LV) load models by aggregating the power demand and the characteristics of the individual households devices into the load model of a household. This is achieved using information from the UK Time Use Survey (TUS) [5] on the activities and everyday habits of people. Profiles of the UK population were created by a Monte Carlo - Markov chain (MCMC) simulation method. These activities were converted into power demand through database, that contains the majority of the possible domestic appliances available in UK and lists all of their power



consumption, electrical characteristics, ownership and usage statistics. The second level of aggregation is able to form the load model of the desired population. Although the main target is to reproduce realistic load models of UK households under the maximum loading conditions, which is considered to be a winter weekend, the methodology can adapt at any location and to be temporally flexible enough to calculate the load model at any period of the year, weekday or weekend.

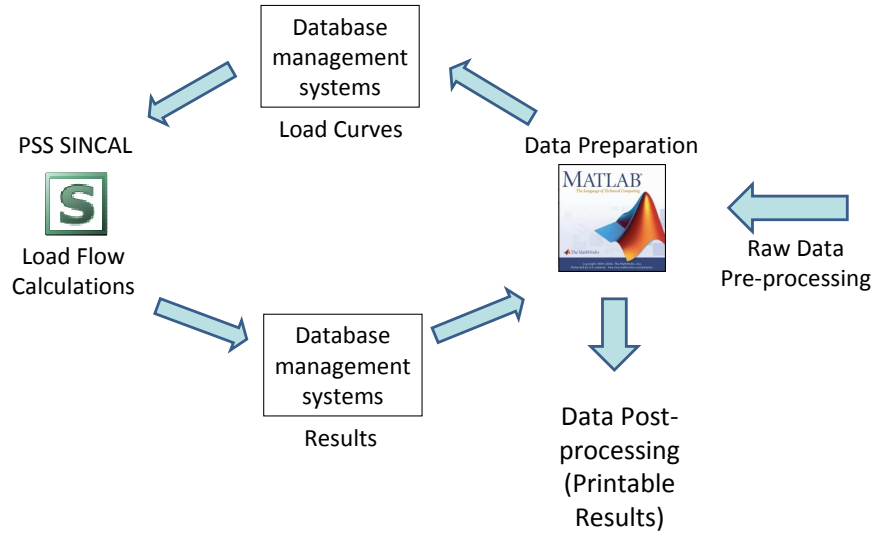
The second objective includes the use of the developed load models to illustrate and comprehend the impact of the altered load mixture on two demand and network management techniques: DSM and conservation voltage reduction (CVR).

The specific research objectives can be summarised as:

- The development of a load modelling tool that provides accurate detailed load profiles with high resolution to represent UK residential power demand.
- A study of the contribution of the various types of loads in operation and power quality of the system.
- An investigation of the impact of the increasing presence of modern appliances on the grid, grouping the modifications into two scenarios: short and long term future loading mixture.
- An assessment of the impact of DSM on network operation using the financial and environmental cost as the motivation that drive the optimisation algorithm.
- A study of possibility of applying CVR at LV residential network and assess the potential benefits in peak power reduction.

The scope and boundaries of the research are defined as:

- The research included in this thesis is primarily focused on the UK residential load sector taking into account the corresponding demographic characteristics.
- The network analysis in all applications use a typical generic UK LV residential highly urban network that is populated only by domestic customers.
- The maximum loading conditions have been used in all cases. However, the developed methodologies may be transferred to any desired population, type of network or time.
- The PSS Sincal® network simulation software was used to conduct the network analysis in all cases using the four-wire system for unbalanced network simulation. The simulation framework that was followed can be summarised in Figure 1.2.



**Figure 1.2:** The simulation framework.

## 1.4 Thesis statement

The individual contributions listed in Section 1.2 are the building elements of the main Thesis of this research, expressed as follows:

A bottom-up, user-inclusive domestic electrical load model may yield high-accuracy aggregated demand profiles, which in turn may facilitate detailed technical, financial and environmental assessment of demand side management strategies.

## 1.5 Acknowledgment of the thesis contributions

The results from this thesis have been presented in three journal papers [6, 7, 8] and four international conference papers [9, 10, 11, 12]. Paper [12], reporting part of the work, received the best paper award at the IEEE Electric Vehicles and Renewable Energy (EVER) International conference 2014.

The main contributions, and the corresponding publications, can be summarised as:

- Compilation and presentation of the characteristics of the majority of the available residential appliances [6].
- Development of the load modelling methodology and validation of its results [7, 9, 10].
- Assessment of the potential benefits from controlling voltage to reduce power demand [11].
- Development of optimisation algorithm to implement DSM actions on wet loads to minimise the economic and environmental cost for customers [8, 12].

## 1.6 Thesis structure

The thesis is divided into seven chapters, whilst additional material, regarding the secondary databases that are required by the developed tool are presented in the Appendices.

Chapter 2 reviews the publicly available literature on the two main subjects and their subcategories addressed in this thesis. The most popular sources of the existing datasets of power demand profiles that are used in energy systems studies are presented and discussed. Then the studies that focus on future alterations of the residential load mixture are reviewed to identify the load categories that are expected to be affected in the coming years. This is followed by clarification of DSM definitions and characteristics. A literature review on the most popular approaches that are found is presented. Finally, a description of the theoretical background of the conservation voltage reduction is shown and the reasons why the existing generic load models do not allow for satisfactory study of this potential peak load reduction technique.

Chapter 3 presents the methodology that was developed to create the load modelling tool. The whole calculation process is described step by step, from the generation of the activity profiles of the customers to the conversion into power demand profiles and, finally, to the calculation of the aggregate load model of each household. All three steps are described thoroughly and are followed by examples for a better explanation of the calculation process. The validation of the model follows, where a large number of developed profiles, 10,000 in order to achieve homogenous sample, is compared against the most common databases that are used. The variation of the results depending on the period of the year is also proven by giving examples from some load categories.

Chapter 4 describes a study on the load replacements due to the introduction of modern appliances. Three designed scenarios, including the base case, are described. The three scenarios are compared first without the participation of the network. Then a network analysis is performed to assess the impact of the assumed modifications on the network operation.

A scenario that includes the implementation of DSM on the results of the scenario that provided the most promising results, and derived from the comparison in Chapter 4, is described in Chapter 5. The methodology that was used to enable the load shifting is described first. Here, two drivers used, minimisation of the generation cost and greenhouse gas (GHG) emissions, are explained. Afterwards, a network analysis is performed for the case that achieved the highest savings among the others.

Chapter 6, presents a study on taking advantage of the CVR implementation on the LV transformer to reduce the power demand during the peak hours. At first, the advantage of using the detailed load models are described indicating the potential periods of the day that the greatest saving is achieved. The setting of the maximum limit of the saving that can be possibly achieved is followed by the implementation of the control algorithm that reduces the voltage level only when it is necessary.

Finally in chapter 7, an overview of the main findings of the research and the contributions to accurate generation of load profiles is presented. The implications and limitations of the research are discussed, while recommendations for further development and improvement of the methodologies of this research are given.

# Literature Review

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### 2.1 Introduction

This chapter describes the background and provides a literature review related to the main topics of the thesis. A description of load models and a summary of the existing load models are presented here. Furthermore, the concept of demand-side management and the implementation of Smart Grids are presented and discussed using the existing research. A synopsis of the studies over the potential of voltage control on the distribution network is also provided.

### 2.2 Residential Load Modelling

The study of power systems and the increasing interest in understanding the effect of the different kind of loads on the operation of the network have led to ongoing research on load modelling. The majority of the existing research has focused on the development of load profiles and less on creating load models that could describe and fully represent the electrical characteristics of the loads. This section reports the most important and recent studies on the development of the load profile and load models.

#### 2.2.1 Residential Load Profiles

For over a half of a century [13, 14], considerable effort has been invested in developing load profiles for the domestic sector for a wide range of power systems studies, network planning [15] and load forecasting [16]. However, domestic load curves have been used for economic [17] and socioeconomic purposes [18] as well. These profiles were developed either by measurements in the field, like [19] or through simulations, e.g. [20], while they differ in their statistical methodology. Their location also varies as there are studies from all over the world which demonstrates the spatial character of a load profile.

A popular modelling technique among the existing studies is to define switch-on probability distribution functions (pdf) and durations of appliance use so as to synthesise active power electricity demand profiles. Field measurements [19, 21] can be used to achieve this as long

as they are sufficiently detailed [22]. An alternative option to define a switch-on pdf is Time Use Survey (TUS) data. This method was used in [23] and was combined with a Markov chain approach to create occupancy profiles. The methodology of this study is very detailed as it is among the few that take into account appliance sharing probability between the occupants and provide both active and reactive power profiles though assuming constant power factor for each type of appliance. The power factor values were obtained by a small number of measurements on the appliances. A similar approach was followed by [24], although a reactive power profile is not produced. An other example of developing residential active power demand profiles which includes appliance use pdf is [25]. This stochastic model starts by defining user availability functions (which is the equivalent of an occupancy model) and when the user is available device use pdfs are used to convert occupancy to electrical loads.

The Monte Carlo simulation technique is also frequently met in the literature, such as [26] and [20]. In the first case, measurements were used to develop the active power demand curves while constant power factor equal to 0.98 is assumed for all loads during the day. In the second study, household current is measured and assigned to household appliances. The identified appliances are defined by number, time and duration of switch-on events. The probabilities of these are calculated and implemented in a Monte Carlo simulation using random number generation. A similar probabilistic method is used in [27] where current measurements are also used and residential active power demand is modelled using a beta distribution.

Another way of forming the active power demand profile of a household is by aggregating the power demand curve of the individual appliances and loads, which is described as a bottom-up approach. Recently, a technique to develop load curves using a bottom-up approach was presented [28], in which appliances are assigned to households based on ownership statistics and switch-on probabilities, that are uniformly and normally distributed throughout the day depending on load type. The appliance characteristics are obtained by measurement. However, statistics of appliance ownership and use could also be used as input data in conjunction with the measurements [29]. In [30], a bottom-up approach is used to develop active power demand profiles and uses probabilistic functions to define model behaviour. The distinction of this approach is that the user is assigned 'human resources', e.g. eyes and ears, to ensure that conflicting activities are not performed simultaneously. Then the activities of all occupants are aggregated into household activities and converted into active power demand profile. A mixture of TUS and questionnaire data is used to set the probability functions.

In a fashion similar to the studies using a bottom-up approach, there are studies that focus on individual appliances or load categories separately [31]. The individually modelled loads are added to the rest of the active power demand and used in studies regarding network operation and technical hitches [32] or load management [33].

Although the above techniques are the most common, there are some studies where less popular modelling approaches are used. An agent based approach is used in [34], where each household

is defined as an agent, and probability distribution functions are used to populate household appliances and use. A survey of user behaviour and device ownership is used as input data. In [35] a ‘random number technique’ was used. Furthermore, [36] proposes a technique that converts pdfs to fuzzy logic in order to create aggregated active power demand curves. Finally, [37] uses a mixture of Gaussian distributions to model active power demand distributions. Power factors are also taken into account but, as in the majority of the literature, constant values are used - 0.95 for residential sector.

The need for more detailed load profiles for more accurate results in power systems studies is visible by the fact that in many of the most recent studies there is some kind of categorisation of the users or the load. In [22] there is a temporal division between seasons and weekdays/weekends. Also, users are characterised as working or non-working occupants, similar to [35] where households are also divided into flats, semi-detached, detached and mid-terraced houses. [24] and [23] have similar categories and additionally the number of occupants is taken into account.

### 2.2.2 Static Load Models

Static load models can be used to describe the electrical characteristics of loads in case of steady-state power flow analysis. Traditionally, all loads are used to be represented by one of the three existing load models:

- constant power (CP)
- constant current (CC)
- constant impedance (CZ)

However, most of the loads and appliances cannot be represented by only one of the above three models. So, in order to increase the level of the detail in load modelling, a mixture of these models is used. The most popular expressions of these mixtures in the literature are the exponential (2.1) and polynomial/ZIP (2.2) load model forms [38, 39]. Although the polynomial load model provides more detail in the representation of modern non-linear loads, the exponential load model is preferred for demonstration purposes because of the single coefficient. However, the conversion from ZIP load model to exponential is straightforward with (2.3) [40].

$$P = P_0 \left( \frac{V}{V_0} \right)^{n_p} \quad (2.1)$$

$$P = P_0 \left[ Z_p \left( \frac{V}{V_0} \right)^2 + I_p \left( \frac{V}{V_0} \right) + P_p \right] \quad (2.2)$$

$$n_p \approx \frac{2 \times Z_p + 1 \times I_p + 0 \times P_p}{Z_p + I_p + P_p} \quad (2.3)$$

where:  $P$  is the active power demand at supply voltage  $V$ ,  $P_0$  is the rated active power demand at nominal supply voltage  $V_0$ ,  $n_p$  is the exponential model active power coefficient and  $Z_p$ ,  $I_p$  and  $P_p$  are the constant impedance, constant current and constant power coefficients of the polynomial model. Similar expressions are used for reactive power:

$$Q = Q_0 \left( \frac{V}{V_0} \right)^{n_q} \quad (2.4)$$

$$Q = Q_0 \left[ Z_q \left( \frac{V}{V_0} \right)^2 + I_q \left( \frac{V}{V_0} \right) + P_q \right] \quad (2.5)$$

where:  $Q$  is the reactive power demand,  $Q_0$  is the rated reactive power demand,  $n_q$  is the exponential model reactive power coefficient and  $Z_q$ ,  $I_q$  and  $P_q$  are the corresponding reactive power coefficients of the polynomial model.

Except for the cases where loads are modelled as one of the traditional load models (e.g. in [41] loads are modelled as 60%CP, 40%CZ or 40%CP, 60%CZ according to the season), the majority of load models that have been used in power system studies [42, 43] are obsolete [2, 44, 45]. Although the existing aggregate values of residential load sector models of total or large parts of the network were sufficient for the research then, an update is needed due to the switch of the research focus from the total, high-level network management to a more localised management of the network and demand. Also, the changes on the technology and load characteristics of the current residential appliances is an extra reason for a more detailed representation of residential load sector [46]. This is even more visible in studies of the residential sector in low voltage (LV) where aggregate, constant values are used for the coefficients of the load models. Three examples of this case are summarised in Table 2.1.

**Table 2.1:** Existing residential load sector models.

Ref	Year	V (kV)	Location	Form	Season	Parameters
[44]	1993	ns	USA	Exp.	S W	$n_p=0.9-1.4, n_q=2.4-2.9$ $n_p=1.5-1.7, n_q=2.5-3.1$
[47]	2004	21	USA	ZIP	ns	$Z_p=0.29, I_p=0.1, P_p=0.61$ $Z_q=3.22, I_q=-4.53, P_q=2.31$
[48]	2008	10	Serbia	Exp.	S W A	$n_p=1.162, n_q=4.016$ $n_p=1.401, n_q=3.460$ $n_p=1.245, n_q=3.899$

where: ns stands for not stated and S, W and A represent summer, winter and annual time period respectively

A component-based load modelling approach has also been implemented to develop a detailed household load model. According to this technique, the various residential loads are analysed into their components and those with similar characteristics are grouped. Table 2.2 presents



the models of the individual load components. Lighting is modelled as incandescent (GIL) or compact fluorescent (CFL). Motor load types are used to represent cold appliances (refrigerators and freezers) and water pumps. Loads that are used for heating, such as space and water heating, electric hobs/ovens and kettles, are assumed to be ideal resistive loads. Consumer electronic devices and information and communication technology (ICT) devices are modelled as "switch-mode power supply" (SMPS). Depending on rated power, electronic devices can be equipped without power factor correction (no-PFC), with passive PFC (p-PFC) or active PFC (a-PFC). These are discussed in more detail in [49, 50].

**Table 2.2:** Polynomial load model coefficients [49, 50].

Load	$PF_1$	Polynomial Model					
		$Z_p$	$I_p$	$P_p$	$Z_q$	$I_q$	$P_q$
GIL	1	0.43	0.69	-0.12	-	-	-
CFL	0.91	-0.01	0.96	0.05	0.1	-0.73	-0.37
RSIR <sub>QT</sub>	0.62	0.10	0.10	0.80	1.40	-0.91	0.50
CSCR <sub>CT</sub>	0.9	0.50	-0.62	1.11	1.54	-1.43	0.89
Resistive	1	1	0	0	-	-	-
SMPS <sub>noPFC</sub>	0.99	0	0	1	-3.63	9.88	-7.25
SMPS <sub>pPFC</sub>	0.97	0	0	1	0.45	-1.44	1.99
SMPS <sub>aPFC</sub>	1	0	0	1	-	-	-

where: SMPS<sub>noPFC/pPFC/aPFC</sub> are SMPS with no-PFC, passive-PFC and active-PFC, RSIR is resistive start-inductor run motor, CSCR is capacitor start-capacitor run motor, subscripts QT/CT are quadratic/constant torque motor loading conditions and  $PF_1$  is displacement power factor.

## 2.3 Demand-side Management (DSM)

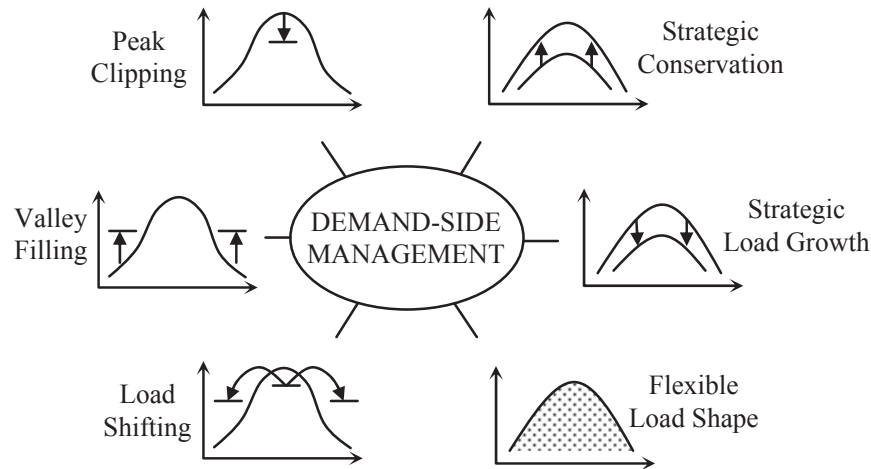
Over the last two decades, there has been intensive research on demand-side management methods which promise solutions in covering and managing the future load. However, the concept is not new as some primitive load management techniques have been applied since the 70's [51, 52] and were evolved into what is launched as DSM strategy.

In [53], DSM is described as the group of actions and techniques that are used to plan, monitor and control the use of electrical energy from customers and help electric utilities to provide efficiently the demanded energy. DSM, through its actions, is tightly related to a number of fields, such as distribution networks' infrastructure, electricity market, distributed generation, smart grids and smart devices [54]. The DSM actions, as seen in Figure 2.1, are categorised in six main categories [54] based on the load shaping effect:

- Peak clipping
- Valley filling
- Load shifting

- Conservation
- Load building
- Flexible load shape

With these load shaping objectives, it can be concluded that the main objective of DSM strategy initially was to make the load curve as flat as possible and improve the process of the generation planning from the utilities point of view. However, this has evolved into an attempt to manipulate the demand curve to match generation, so modern systems are “generation driven” instead of “demand driven” that were in the past. This would also allow to take into advantage the increased penetration of renewable energy, as efficiently as possible.



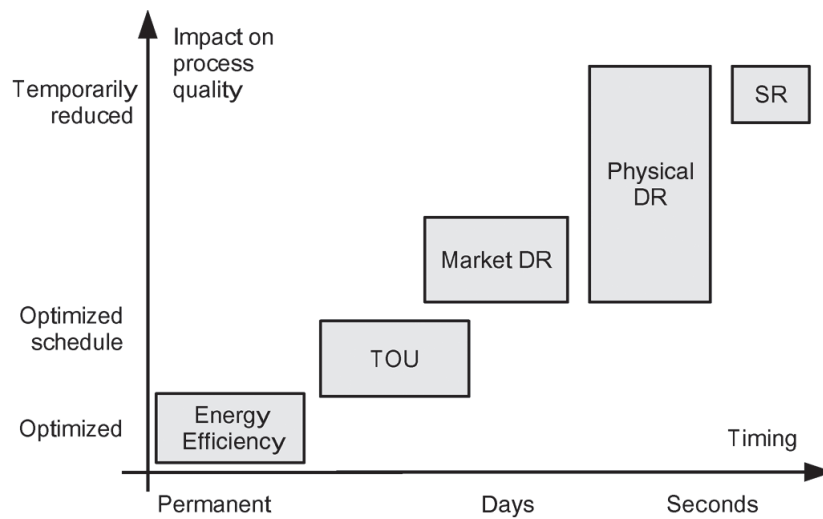
**Figure 2.1:** The six categories of DSM actions [54, 55].

Another categorisation of DSM, depending on the time response and the impact of the applied measures on the customer, can be the following:

- Energy Efficiency (EE).
- Time of Use (TOU).
- Demand Response (DR).
- Spinning Reserve (SR).

As the Figure 2.2 demonstrates, the faster the changes are processed and applied, the more unwanted impact they potentially have onto the customers lifestyle and habits [56]. For a successful implementation of DSM in the future, it is required to reduce the cost of the required infrastructure, pump power and optimise human comfort or health in a household.

The main principles of DSM actions and how the customer-to-grid interaction is performed are presented in [56]. Through this interaction, DSM can provide a lot of benefits in all four stages of the electricity system: generation, transmission, distribution and consumption, but there are a few issues that need to be taken into account. The benefits, according to [57], are summarised



**Figure 2.2:** Categorisation of DSM according to timing and impact as presented in [56].

here:

- Generation
  - Reduction of the required generation capacity margin
  - Increase of generation efficiency and drop of generation fuel cost
- Transmission
  - Improvement of transmission grid investment and operation efficiency
  - Ability to deal with technical failures and handle massive power transfers
- Distribution
  - Real time managing of supply requirements
  - Distributed generation introduction will increase the level of control in distribution networks
- Consumption
  - Reduction of the large variation of demand during the day and year

As for the challenges, [57] lists the following:

- Lack of ICT infrastructure
- DSM makes the system operation more complex
- Electricity market is not ready for DSM
- Load diversity and possibility of loads reconnection simultaneously

The results and the methodology of DSM studies are mainly influenced by the selected driver that is used for the decision process. The majority of the existing literature uses financial criteria to perform the necessary DSM actions [58, 59]. In [60], the valley filling DSM action is driven by the generation cost to achieve the targets of the study on voltage profile improvement and

minimisation of losses. The cost profile can be either constant or variable during the year according to the season [61].

Another popular driver of DSM is the minimisation of the environmental impact of the electrical system, which is usually quantified by using greenhouse gas (GHG) emissions. The continuously increasing awareness for the climate change has also been introduced in power systems and the implementation of concepts, such as DSM, is presented as one of the solutions [62, 63]. The majority of the existing research focus on the potential effect of DSM on the load demand in total without analysing this result in detail or from a lower voltage level [64, 65]. Although the general outcome is that the reduction in GHG emissions is not considerable [66, 67], the calculation of savings cannot be precise enough unless the study is performed in a low-voltage level including the human lifestyle factor.

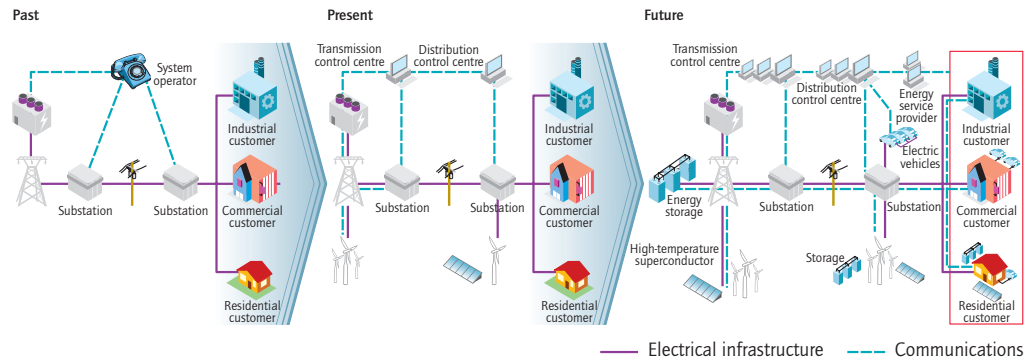
The DSM studies that focus on LV distribution system, apply their techniques on certain load categories and not just in aggregated amounts of energy as it usually happens in higher voltage level studies [57, 62, 68, 69, 70]. The most common appliances that are chosen for control are heating and heat pumps [71, 72, 73, 74], electric vehicles (EV's) [75, 76] and wet loads (i.e. washing machines, dishwashers etc.) [72, 77].

### 2.3.1 Smart Grids

A smart grid is an electricity network that uses digital and other advanced technologies to monitor and manage the transport of electricity from all generation sources to meet the varying electricity demands of end-users. Smart grids co-ordinate the needs and capabilities of all generators, grid operators, end-users and electricity market stakeholders to operate all parts of the system as efficiently as possible, minimising costs and environmental impacts while maximising system reliability, resilience and stability.

Smart grids include the whole electricity network, including transmission and distribution systems, and interact with generation, storage and customers. As it can be seen in Figure 2.3, the present energy networks is already supported by a secondary communication network that ensures the efficient energy delivery to the customer. Although the upgrade of the electricity system has begun in some areas worldwide, all countries will have to invest in significant changes and further development of the existing communications network, planning and utilisation of new technologies in renewable energy generation and storage in order to be able to support a smarter grid. The evolving set of technologies, such as DSM, that form smart grids will be established in different proportions in a variety of settings around the world, according to local commercial availability, compatibility with existing technologies, regulatory developments and investment frameworks.

The smart grid should be designed in such a way that will provide thorough grid supervision and take advantage of most of its components, resulting in a system of optimised performance



**Figure 2.3:** The evolution of smart grids in time from [78].

and security and simultaneously minimising the operational cost. The developed system is essential to allow for immediate management of any emergency or unexpected loads and market participants (generation or storage) instantaneously [79]. The key characteristics of such grid are expected to be able to self-heal; to provide a user-friendly environment that will empower and incorporate the consumer; be resistant in cyber and even physical attacks to key parts of the network; provide high power quality; and finally to accommodate a wide variety of generation options, which fully enables maturing electricity markets, and optimises all grid assets. With the proper smart grid design, life cycle management, cost containment, and end-to-end power delivery will be improved for a more efficient power network [80].

Requirements of the promotion of smart grids:

- All-inclusive, automated communication among the participants of the electric network.
- Technologies that provide advanced sensing and measurements capabilities.
- Automated management for power supply and maintenance.
- Improved control panels and decision-making process software.

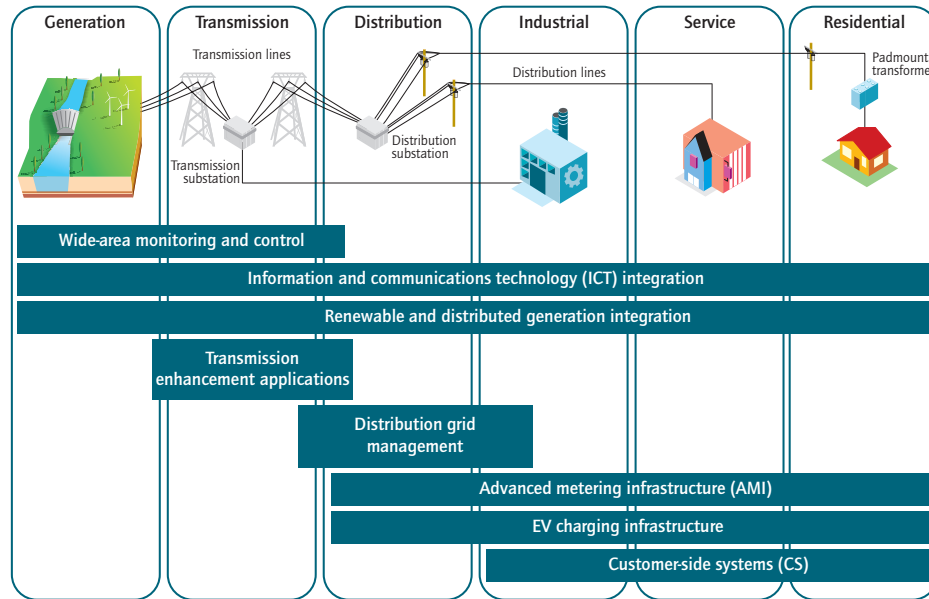
In order to allow for the employment and development of smart grids, a lot of technology areas related to electrical systems need to be fully optimised, as seen in Figure 2.4 and described in detail in [78]. However not all of them are immediately needed to upgrade the grid. Some of the key challenges that need to be faced in priority [81, 82, 83]:

**Environmental:** Challenges related not only to the reduction of the greenhouse gas emissions caused by electricity generation and consumption, but also to the effect of the environmental and natural factors that could destroy parts of the grid and affect its reliability and operation.

**Utilities/Customers needs:** Integrated system operation technologies and power market policies need to be developed to maintain the transparency of the competitive market. Customer satisfaction should be improved by providing high quality in the lowest price and suggestions on scheduling the power consumption when possible, while customers should be allowed to interact with the grid.

**Infrastructure:** The quickly aging components of the existing electricity transmission system consist of significant defect and more investments for improvements are required. This situation deteriorates because of the increasing load demands and the network congestion. The online real-time analysis tools, monitoring and control of extensive networks, and fast and accurate protections are needed to enhance the network reliability.

**Innovative technologies:** Development of the appropriate means that will integrate the concept of smart grids into the existing system and take advantage of their features.



**Figure 2.4:** The technology areas that need to be fully optimised for the establishment of smart grids from [78].

The related goals of intelligent functions in smart grid design, as they are presented in [79], can be summarised into the following:

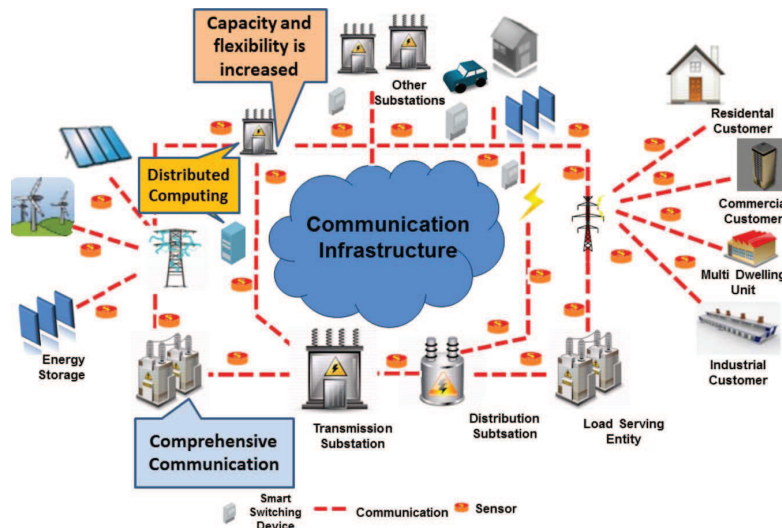
- Real-time angle and voltage monitoring and mitigation of the possibility of power failure using measured data.
- Reactive power control based on sophisticated management framework.
- Fault analysis and reconfiguration plans of action based on automated switching operations.
- Power generation and consumption balance using automated switching operation to supply loads while controlling frequency and oscillations, and minimise demand interruption. This can also be achieved through the establishment of microgrids by providing smart and efficient communication among the local networks.
- Distributed generation (DG) and DSM through DR strategy for peak shaving. These also include increased proliferation and control of renewable energy resources (RERs).

### 2.3.2 Smart metering

As it was mentioned in the previous section, the development of the necessary infrastructure and the technologies that will be used for the monitoring and the control of smart grids is a priority. An intelligent network of sensors and actuators would allow for the effective application of DSM and a reliable balancing framework between the generation and consumption of the electrical energy.

Over the years, significant amount of time has been spent on the research to solve the challenges that appear towards the integration of smart metering infrastructure. The incompatibility between the power and the communication networks and the necessity for different approaches is discussed in [84]. The majority of the studies agree that the most efficient way to control such system, where an electricity network is widely dispersed with millions of consumers and producers connected on different grid levels, is a distributed control mechanism [83]. Basically, two types of information infrastructure are needed for information flow in a smart grid system. The first flow is from sensor and electrical appliances to smart meters and the second is between smart meters and the utility's data centers. As suggested in [85], the first data flow can be accomplished through power line communication or wireless communications, such as ZigBee, 6LowPAN, Z-wave, and others. For the second information flow, cellular technologies or the Internet can be used. Nevertheless, there are key limiting factors that should be taken into account in the smart metering deployment process, such as time of deployment, operational costs, the availability of the technology and rural/urban or indoor/outdoor environment, etc. The technology choice that fits one environment may not be suitable for the other.

Whichever communication methodology, or combination of methodologies, dominates, which



**Figure 2.5:** The operation of smart grids highly depends on the communication infrastructure from [86].

includes the media and the protocols that will be developed, will have to be able to be robust enough to accommodate new media, as they emerge from the communication industries, which will have the technical requirements to handle and process the enormous amount of data that will occur. Communication protocols with standard semantic models for each domain of the smart grid have to be developed that will be capable of secure inter-domain information exchange [87].

The meters will replace the present meters, and therefore will not cause any direct design implications to the buildings. However, these meters will make a large amount of data available to operations and planning, which can potentially be used to achieve better reliability and better asset management [88]. Perhaps the biggest change that advanced meters will enable is in the area of real-time rates. True real time rates will tend to balance distribution system loading patterns [89]. In additions, these meters will enable automatic demand response (DR) by interfacing with smart appliances. Managing smart grid/metering projects is difficult due to the sheer size and complexity of the number of data points. For example, a typical DR project requires [90]:

- secure and reliable system that provides unobstructed communication between the involved parties.
- ability for various utilities to participate in the energy market by bidding and interacting to prices in real time, actions which will be visible to all parties.
- facility to schedule and implement the transactions that parties have agreed to do.
- measurement and verification of the above actions through established protocols.
- automated processes for billing, collection, providing statistical records and dispute resolution.

Regarding the management of a smart metering/pricing project, the following are required:

- a range of services and tariffs that vary by time of use and potentially by type of application to meet customers' needs.
- services that provide adequate metering data management.
- new systems for billing and settlement that can also educate the customers towards proper consumption of energy and provide suggestions.
- new applications and interfaces capable of supporting the new metering, educating, pricing, and billing services.

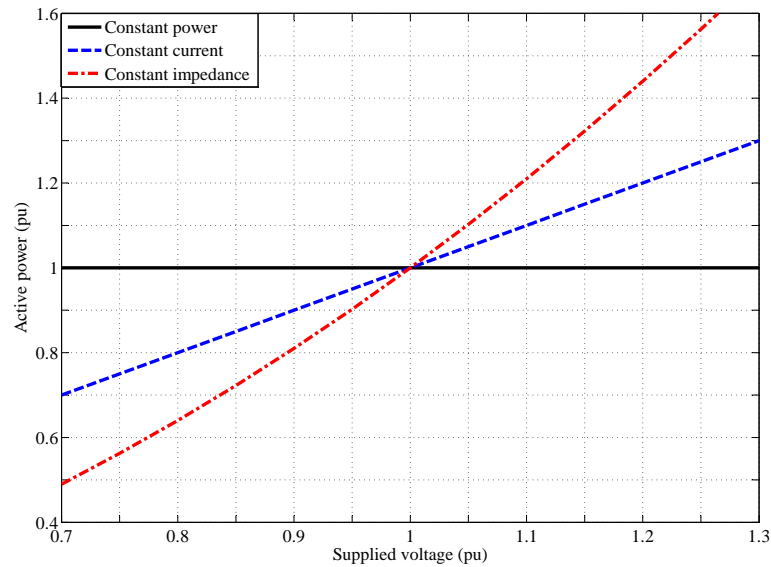


## 2.4 Voltage control

Maintaining supply voltage within the required limits is one of the key requirements of the electrical power system. To achieve this, various devices, e.g. static voltage-ampere reactive (VAR) units or on load tap changing transformers (OLTC), are installed throughout the system to maintain the voltage magnitude within operational limits. Previous research has shown that it is possible to reduce the active power demand of the load by using these voltage control devices to lower the voltage magnitude during hours of high demand [91, 92]. Although, it is often said that a ‘1% voltage drop will result in a 1% decrease in power demand’ [93], the power reduction cannot be easily quantified. This is confirmed by previous research, from which two general conclusions can be drawn [93, 94, 95]:

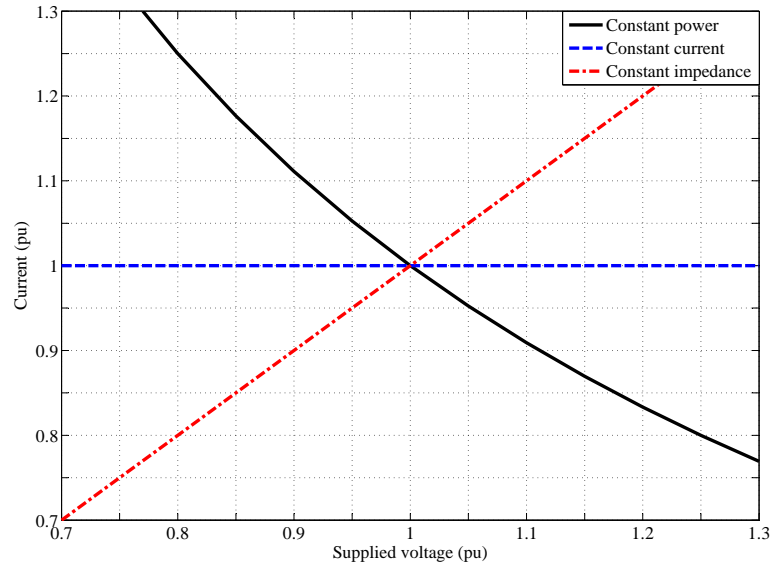
- The typical active power reduction is between 0.4-1% per 1% voltage reduction
- The results are hard to predict and are influenced by the location, time of day and time of year

The electrical characteristics of power system loads will change as a function of the supply conditions, i.e. voltage magnitude and frequency. The three load types that are described in 2.2.2 are shown in Figure 2.6.



**Figure 2.6:** The P-V curves of the three traditional static load models.

The corresponding changes in load current magnitude (assuming a dc power flow) are also shown in Figure 2.7. These curves clearly illustrate why the type of load connected will influence the power demand savings for voltage reduction. For example, although the power demand of a constant power load will not change by reducing the voltage, the current will increase, which will result in higher losses across the network impedance.



**Figure 2.7:** The effect of the three traditional static load models on current for variable supplied voltage.

Previous research in this area is based solely on field tests and measurements at distribution system substations [91, 92, 93, 96] or in individual commercial and residential buildings [94, 95].

## 2.5 Conclusion

This chapter has presented a general overview of the main research areas of this thesis. A review of existing residential load profiling approaches is presented and the gaps in load modelling are discussed. The key characteristics of the DSM strategy and the current research towards the efficient implementation of DSM actions are also summarised. Furthermore, a description of the concept of CVR on the distribution network along with the studies around it is also provided.

The review of the existing literature has shown that an advanced study of DSM requires the implementation of the human factor. Thus, there is a need for a better representation of the residential load sector in low-voltage level that includes the customers' characteristics and usage profiles. The load modelling framework should be spatial and temporal dependable to better show the differences in demand among the countries and seasons.

# Development of a Residential Load Model Tool

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### 3.1 Introduction

In this chapter, the power conversion model that has been developed to create complete load models of residential individual households is described. The bottom-up modelling approach adopts a Markov chain Monte Carlo (MCMC) approach to create activities and power demand profiles. These profiles are combined with the electrical characteristics of the operation of the household appliances, to develop detailed models of residential loads suitable for the analysis of smart grid applications and low-voltage (LV) demand side management.

The contribution of the research described here is the ability to develop detailed time-varying models of individual households and aggregate LV residential sector load demand. The software, which implements the modelling strategy, is flexible and allows for spatial and temporal variations. It uses a number of separate databases about household type and size, statistics of ownership and use of appliances, ambient conditions etc., to produce daily models of the power demand of individual household that can be aggregated and used in large number of network or demand management studies.

Since it is the user behaviour that drives the electrical power demand, the modelling philosophy starts from the behaviour of individual users which are represented in a MCMC modelling approach. The user activity profiles are then converted into active and reactive power demand profiles and the corresponding load models by using a large database of load statistics and a library of detailed load models of the individual load components which have been developed in previous research [6, 7, 8]. The methodology is implemented using the UK residential load sector as an example, and the various stages of the modelling process are validated against available UK statistics, although the approach is generic and applicable to other countries.

The chapter is structured as follows: an overview of the load development methodology is described in Section 3.2 and the three stages of the tool are illustrated in detail in Sections 3.3-3.5. The model is validated by using the UK residential load sector example in Section 3.6, although the approach is more widely applicable. The conclusions are discussed in Section 3.7.

The developed software is made freely available for use by the community at [97].

### 3.2 Load model development methodology

In the residential load sector, the power demand is driven by a large number of factors that need to be taken into account in the development of a modelling tool. The users' behaviour, the characteristics of the dwellings and the appliances available in them are some of these factors. Furthermore, the time of year, with the different ambient conditions, can also affect the demand.

Here, the users' behaviour and daily activities are the basis of this load modelling framework and a significant pioneering approach as the human factor is not usually involved to that extent. Real activity diaries have been grouped and processed using the MCMC modelling method to reproduce realistic activities profiles that characterise the population and area that is studied.

The size of each household (HH) is defined by the number of the occupants  $m$  and the user type of each occupant. Occupants are classified into the two categories 'working' and 'not working', based on their employment status. Children old enough to attend school, thus out of house during day, are labelled as 'working' occupants. Therefore, there are  $m + 1$  possible occupant combinations for each household size, e.g. household size one can have zero or one working occupant. This classification allows for the separate study of weekdays and weekends.

The mixture of appliances in each household is fundamentally connected to the power demand. The vast number of different appliances with different characteristics necessitates a appliances database limited to the most frequently met appliances. These appliances are treated according to their characteristics and nature, grouping them into categories. The seasonal variation of the operation of some loads indicates the necessity of including the weather conditions at different time of year in the tool.

The modelling approach, as presented in Figure 3.1, is summarised into these three stages:

1. user activity modelling;
2. conversion of user activities to electrical appliance use;
3. aggregation of the electrical appliances to build household power demand profiles and load models.

Figure 3.1 displays the information flows in the modelling framework. The input variables are configured by user defined parameters which determine the aggregate size, the aggregate composition, the day of the week and the month of the year. The simulation time step for user activity modelling is 10min, due to the available input data, and is reduced to 1min during the conversion to power demand to more accurately capture the short term variations in load use.

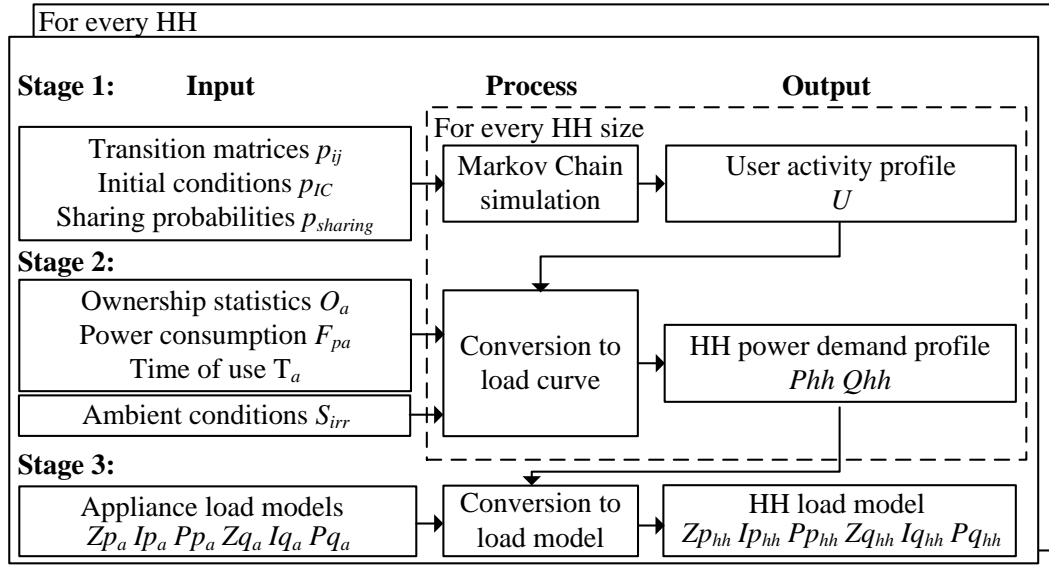


Figure 3.1: Load model development work flow [7].

### 3.3 Stage 1: User activity modelling

The simulation of human behaviour and activities at home is a very difficult task considering the limited available large-scale surveys on the subject. Time Use Surveys (TUS) is a well-known available source of user activity information including a wide range of secondary, supplementary information. TUS database includes studies for a large number of countries [5] allowing profiling in these countries.

UK TUS includes hundreds of different variations of daily activities including activities that people were doing outside the house, such as going out to work or for entertainment that are not related to the residential load modelling. The wide database of activities was filtered and 13 user activity states resulted that describe the majority of possible activities at home [7]. Table 3.1 contains further information on the defined user activity states. As it can be seen, the activities have been divided according to those which require electricity, those that do not necessarily need electricity to be conducted and those which do not involve any electrical use. There is also a distinction between the activities which imply that there is a possibility that more than one occupant are participating and those which do not.

The flow chart of stage 1 has been isolated and is shown in Figure 3.2. In order to model the user behaviour, a combined MCMC algorithm is used to synthesise the user activity profiles  $U$ . A combined MCMC is a stochastic simulation technique that is used for sampling from probability distributions using Markov chains. Monte Carlo method is adding the necessary randomness in the selection of the activity at each time step, while the Markov Chain simulation was used in order to create the complete daily activity profile.

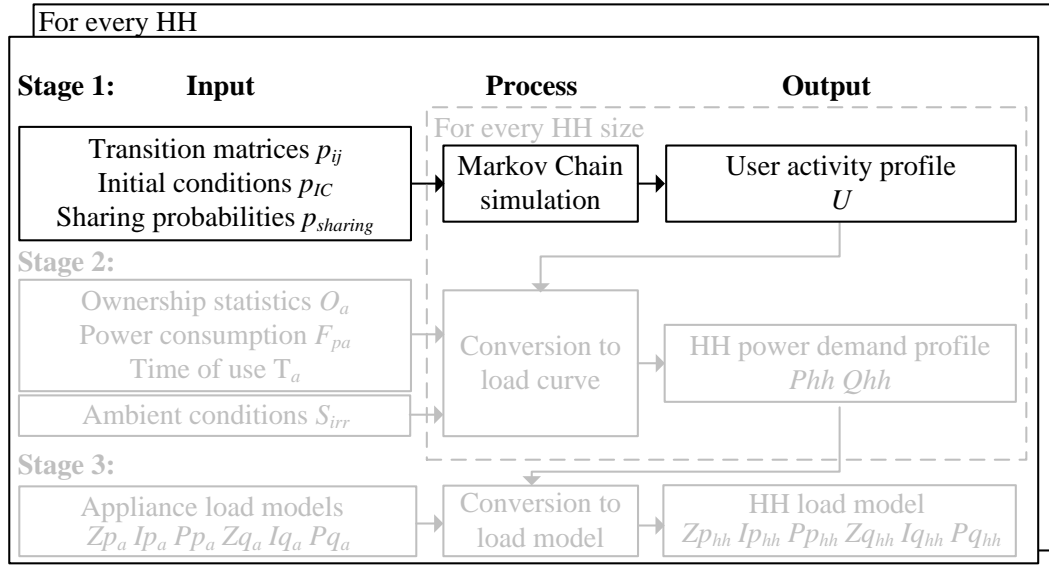


Figure 3.2: Work flow of stage 1.

Table 3.1: User activity state definitions.

User activity state id.	Definition	Electrical Use	Appliance Sharing
1	Non-electrical activity in home	N	n/a
2	Sleeping	N	n/a
3	Wash/dress	Y/N	N
4	Food preparation	Y/N	N
5	Dishwashing	Y/N	N
6	Cleaning house	Y/N	N
7	Laundry	Y/N	N
8	Ironing	Y	N
9	Computing	Y	Y/N
10	Watching TV	Y	Y/N
11	Watching video/DVD	Y	Y/N
12	Listening to music/radio	Y	Y/N
13	Out of house	N	n/a

where: Y - yes, N - no, n/a - not applicable

For the purposes of the tool, one MC transition probability distribution is developed for each time step and includes the probability of switching (or not) between the user activity states to represent the source data and it is given by (3.1). Thus, 143 transition matrices, each containing 13x13 elements for the 13 individual activity states, have been developed, one for every transition in a one-day diary of 10 minutes slots. Furthermore, different probability distributions have been developed for the different types of day or the various categories of occupants resulting in separate sets of transition matrices for each household size and user type. To give an example

of the process, if it has been assigned by the model that, at 3:00 am of a working day in a home of a single, working person, this person is sleeping, then is more likely that at 3:10 am they will be still sleeping, although another activity, such as waking up and going to the bathroom or to the kitchen (both probably involve turning on some lights, thus using electrical energy) cannot be excluded.

$$p_{ij}(t) = \frac{\sum_{j=1}^J n_{ij}}{n_i(t)} \quad \forall i, t \quad (3.1)$$

where:  $p_{ij}(t)$  is the transition probability from state  $i$  to state  $j$ , including  $i=j$ , between time  $t$  and  $t+1$ ,  $n_{ij}(t)$  is the number of transitions from state  $i$  to state  $j$  between  $t$  and  $t+1$ ,  $n_i(t)$  is the total number of transitions from state  $i$  between  $t$  and  $t+1$  and  $J$  is the total number of activity states.

The process of development of the activity profile starts from the selection of the first temporally activity according to the probabilities of initial conditions  $p_{IC}$  which is slightly different from the transition matrices as there is no activity that precedes. All the initial conditions of the participating diaries with similar demographic characteristics were gathered and the probabilities of choosing one of them were calculated. The rest of the activity profile of each occupant is formed by selecting the activity of each time step according to the developed transition probability distributions as described above [7].

In the case of multiple occupancy households, the possibility that more than one occupant could use certain appliances at any given time is taken into account. To achieve this, the device sharing probability is required and it is calculated by using the data from the variable regarding the activity sharing from UK TUS. Therefore, if two or more occupants of the same household are found to have the same activity state and share it according to the corresponding variable at the same time step, it is assumed that the electrical appliance is shared. Then, the activity is assigned only to one of the occupants. The device sharing probability  $p_{sharing}$  is calculated by the ratio of users having the same activity and are sharing the activity to the users who have only the same activity. An algorithm identifies every time period when multiple users have the same activity and compares the  $p_{sharing}$  against a randomly generated uniform number  $r$ . Further information in [7].

Apart from the activity profiles, additional information is given to the next stage of the tool regarding the energy saving habits of the customers. Customers are classified into three categories according to their intention of using the stand-by mode in their electronic devices. The three categories of users are those who never use the stand-by mode (the appliances are either on or off), those who always leave the appliances in stand-by mode when not in use and those who use stand-by mode between the operations but turn them off at the end of the day.

### 3.4 Stage 2: Conversion to electrical power demand

The second stage includes the development of the power demand time series and the ZIP load model of individual households. At this stage, the appliance mixture of the households is selected and the required ambient conditions are defined. Afterwards, these data are combined with the user activity time series that were acquired from the previous stage. The work flow of this stage is presented in Figure 3.3.

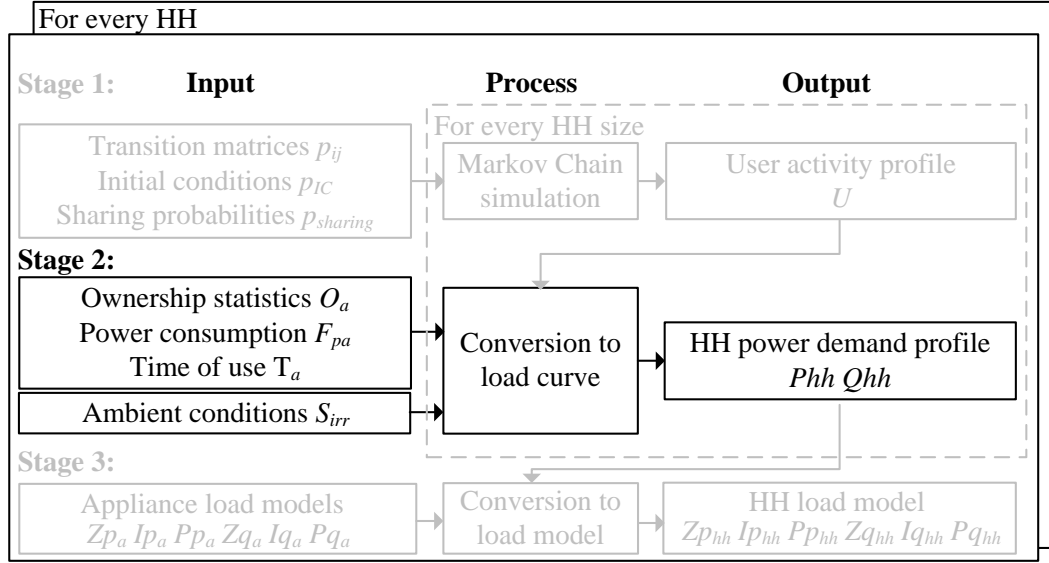


Figure 3.3: Work flow of stage 2.

In order to acquire the data described above and form the power demand model, two databases have been developed that refer to the UK statistics. These databases are:

1. Appliances library
2. Ambient conditions database

#### 3.4.1 Auxiliary Databases

The appliances library includes the most common residential loads divided into nine main categories according to their operational characteristics and use. These categories are cold loads, wet loads electric shower, consumer electronics (CE), information and communication technology devices (ICT), cooking loads, housework appliances, lighting and electric heating loads.

Cold loads include all refrigerators and freezers in four groups according to their characteristics. Wet loads describe the appliances that are involved in laundry and dish-washing activities. The electric shower is a separate category, although it is usually considered as a wet load. The next two categories cover the consumer electronics (CE) and information and communications



technology (ICT) loads. These appliances are frequently used during the day, despite their low power consumption. The cooking appliances category includes the majority of the energy intensive units of a kitchen equipment. The loads that are used for housework activities, such as vacuum cleaners and steam irons, form the housework loads category.

The last two categories referred to the power consumed for lighting and heating. The power demand of these loads is dependent on the presence of people in house and the environmental conditions. The ambient conditions database includes the variation of global solar irradiance during a typical day of each month and the external temperature. In case of lighting, each month has different amount of sunshine per time during the day. In the model an average daily solar irradiance per month is used and these data have been acquired from the Centre for Renewable Energy Systems Technology (CREST) solar irradiance database [98]. Regarding the electrical heating, the average minimum and maximum external temperature data acquired from UK Met Office [99] are considered to calculate the heating requirements at each month.

A summary of the electrical characteristics of the load categories is included in the Appendix A. On the other hand, the average hourly global solar irradiance per month during winter and summer months are presented in Appendix B.

The library is divided into the following categories with their corresponding appliances:

- Cold loads
- Wet loads
  - Washing machine
  - Tumble-dryer
  - Washing dryer
  - Dishwasher
- Electric shower
- Consumer electronics (CE)
  - TVs
  - Set-top box
  - Game consoles
  - Audio Hi-Fi
- Information and communications technology (ICT) loads
  - Desktops
  - Monitors
  - Laptops
  - Office equipment
  - Router
  - Phone/FAX
- Cooking loads
  - Electric hob

- Extracting hood
- Electric oven
- Microwave oven
- Food processor
- Toaster
- Housework loads
  - Vacuum cleaner
  - Iron
- Lighting
- Heating

The appliances library includes the majority of possible domestic appliances that can be found in the UK with their electrical characteristics. It contains device ownership, usage, operating power range and standby power statistics by combining previous studies and manufacturers' datasheets [6]. The database also includes representation of the different operating phases of appliances, e.g. change in power demand during washing machine operating cycle, which are maintained within the developed time varying load models. These data are supplemented with the typical displacement power factor value and the electrical load model.

#### 3.4.1.1 Cold loads

"Cold" load covers all types of refrigerators and freezers. These appliances may be divided into four groups based on size and technical features [100]: group 1 includes small fridges (2 to 3 shelves) with or without a small freezer compartment (Category 1 to 6); group 2 is defined as larger fridges (>3 shelves) with separate freezer section (Category 7 or 10). Stand-alone upright freezers are classified as group 3 (Category 8), while chest freezers are group 4 (Category 9). A review of the consumption, operation and ownership statistics is included at the end of this section in Table A.1.

##### *Technical description*

These devices operate by circulating a refrigerant which absorbs heat from within the device and expends this via external heat exchange pipes. This cycle requires the refrigerant to change state, i.e. from gas to liquid and liquid to gas, and is achieved by a compressor and an expansion valve. The electrical demand is a result of the single-phase induction motor (SPIM) used to drive the compressor. This will cycle on and off as a result of thermostatic control to maintain the desired temperature, the typical cycle will last three quarters of an hour (with a duty ratio of approximately 0.33)[101].

As the compressors used in such devices do not require high starting or running torque, it is expected that 100% of this load uses resistor start - inductor run (RSIR) SPIMs. The motor load is a reciprocating compressor which behaves as a constant torque (CT) mechanical load [102].

The power demand in operation stage ("on period") varies between 25 to 252 W depending on the appliance and will not consume any power during in the "off period" [100, 103]. For all "cold" loads, the distribution of the rated power is considered to be normal.

#### *Ownership statistics*

In the UK, every household will contain at least one "cold" load, defined as the primary device, and around a quarter of all households will have a secondary appliance [100].

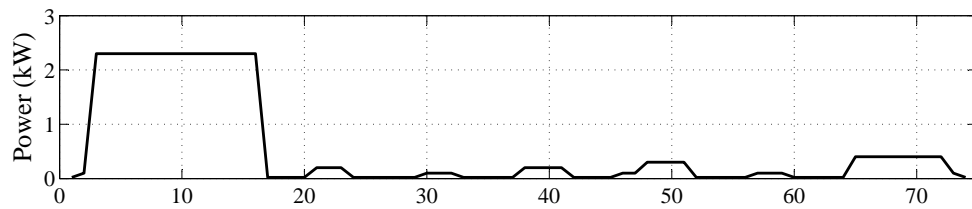
For the main/primary device, 20.7% of fridges are within group 1 and the rest 79.3% are from group 2. For the secondary refrigerator, a smaller appliance, both in terms of physical size and rated power, is mainly used since they consist of 80% of the total number. For freezers, most households have an upright freezer (91.2%) and 33% possess a chest freezer.

#### **3.4.1.2 Wet loads**

The "wet" load type consists of dishwashers, washing machines, tumble dryers and combined appliances, i.e. washer dryers. These appliances have specific operation cycles that vary in time duration, power consumption and model according to the device.

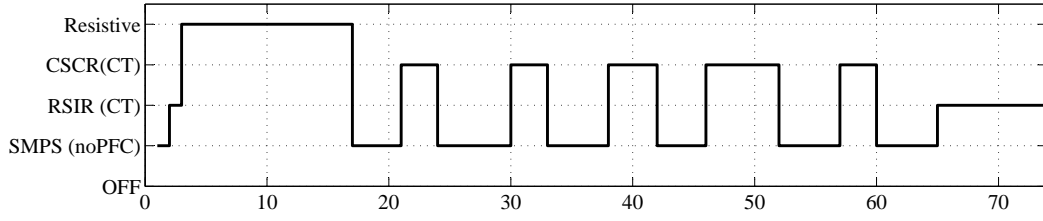
#### *Technical description*

*Washing machines* The operation cycle of washing machines consists of two main stages. During the first stage, water is pumped into the drum and heated up to the required temperature using an ohmic heating element. In the next stage of operation, a sequence of drum rotations are performed with respect to the chosen cycle settings. The drum rotations will be alternated with pumping of fresh water and flushing of water from the drum. The duration of the cycle depends on the selected washing programme and temperature and it may last from 15 min up to 3 hours [101]. However, the typical cycle lasts for 75 minutes [31, 101]. The load model variation of a typical cycle of a washing machine is depicted in Figure 3.5.



**Figure 3.4:** The operation cycle of washing machines.

The rated power of the heating element varies between 1.8 kW to 2.5 kW [101] and is modelled as an ideal resistive load. The SPIM utilised to drive drum rotation is considered capacitor start - capacitor run motor with constant torque ( $CSR_{CT}$ ) due to the high running torque that is required. The centrifugal water pump will present a quadrature torque to the motor and is

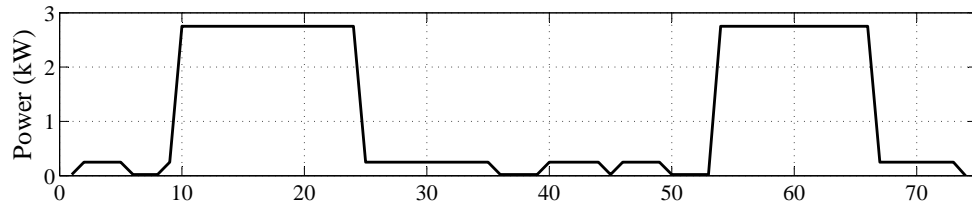


**Figure 3.5:** The model variation during the operation of washing machines.

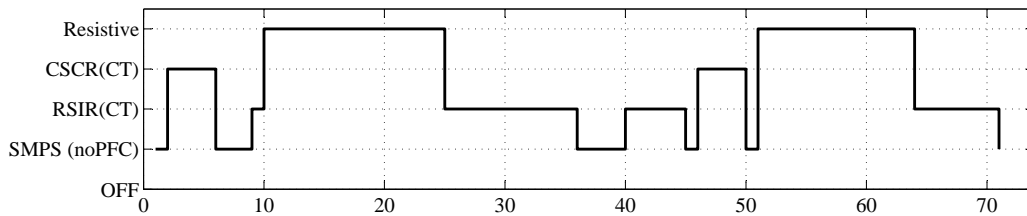
modelled as  $CSR_{QT}$  [102]. The power demand of the electronic control system of the device is very low and is assumed to include basic electronic components, and is, therefore, modelled as  $SMPS_{noPFC}$ .

*Dishwashers* The dishwasher operation will contain three main stages. In the first stage, water is pumped into the device and heated to the required temperature. This is followed by several repetitions, as set by the specific operating setting, of the cleaning process. In this stage, water is supplied to a spray fan element within the device. During the last stage, fresh water is drawn into the device and heated to complete the cleaning process. The duration of the cycle depends on the selected washing program and temperature and it may last from 15 min up to 3 hours [101]. However, the typical cycle lasts for 75 minutes [31, 101].

As with the washing machine, the rated power of the heating element varies between 1.8 kW to 2.5 kW [101] and the internal water pump is modelled as  $CSR_{QT}$ . Due to the lower running torque requirements it is assumed that the rotating cleaning fans does not include a run capacitor, i.e. it is modelled as  $RSIR_{CT}$  load category. The power and load model variation of a typical dishwasher are depicted in Figures 3.6 and 3.7 respectively.



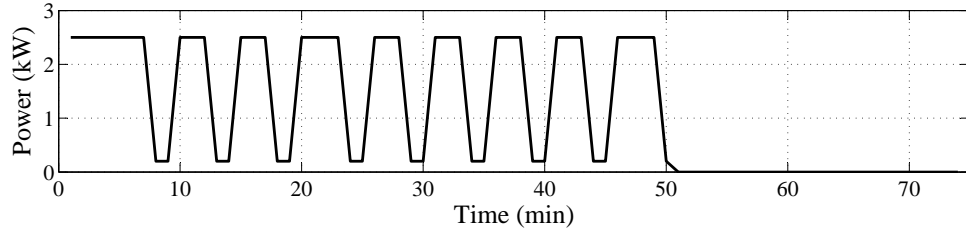
**Figure 3.6:** The operation cycle of dishwashers.



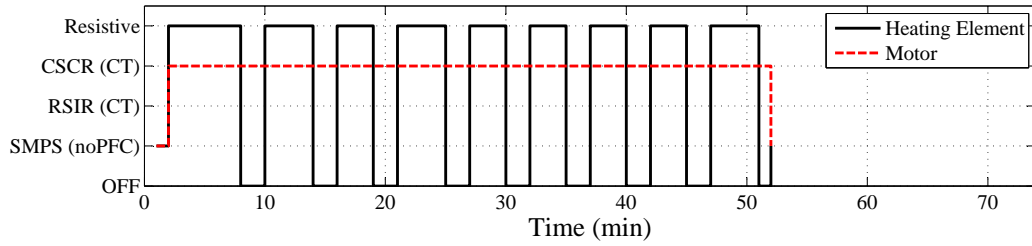
**Figure 3.7:** The model variation during the operation of dishwashers.

*Tumble dryers* The typical tumble dryer contains only two main electrical components: a

resistive heating element and a SPIM to drive drum rotation. The typical cycle consists of a periodic heating of the air within the appliance whilst the drum keeps rotating for the duration of the task [101, 104]. The typical cycle lasts for 52 minutes [101]. The rated power of the resistive heating element varies between 2 - 2.5 kW [101], while the motor for the drum rotation is modelled as  $RSCR_{CT}$  due to the high running torque requirements (Figure 3.9).

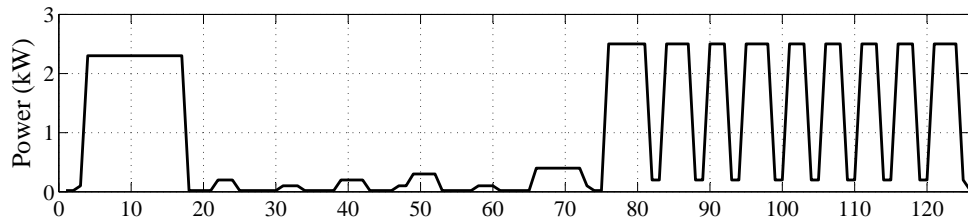


**Figure 3.8:** The operation cycle of tumble dryers.

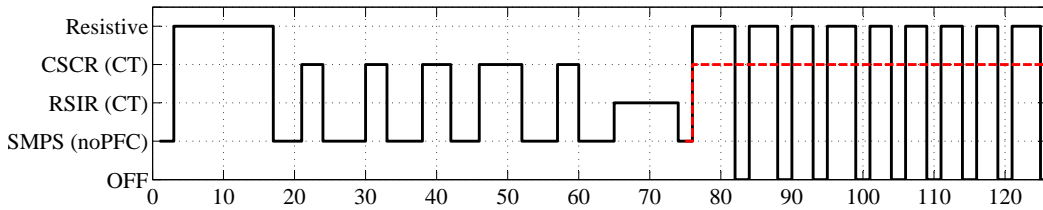


**Figure 3.9:** The model variation during the operation of tumble dryers.

*Washer dryer* A washer dryer is a washing machine that offers additional drying facilities, similar to those performed in tumble-dryers. As such, it is assumed that the device operation will consist of the typical operating cycle of a washing machine followed by the typical operating cycle of the tumble-dryer.



**Figure 3.10:** The operation cycle of washing dryers.



**Figure 3.11:** The model variation during the operation of washing dryers.

*Ownership statistics*

The washing machine ownership in the UK is very high (around 93%), while the penetration of dishwashers is more modest (about 35%) [1, 105]. As for the tumble dryers, about 69% of UK households are equipped with one [1]. The ownership statistics of washing machines and tumble dryers include the washer dryers.

**3.4.1.3 Consumer electronics**

The consumer electronics load type include a large number of different load types. TVs, VCR/DVD players, set-top boxes and all variants of power supplies units (PSU) are classified as consumer electronics. Outwith TVs, the majority of appliances are of low rated powers and can be simplified for modelling purposes. However, TV load requires more careful consideration.

*Technical description*

From an electrical viewpoint, the required operation of all consumer electronic devices is identical. As they all require dc voltage to operate, all consumer electronic appliances require a SMPS to convert the ac supply voltage. Variations will be introduced based on the rated power of the device and the electrical circuits required to satisfy harmonic legislation, defined in [106]. However, all of these devices will present a constant active power load on the power network.

*Low-power and supplementary devices* All low-power and supplementary appliances, i.e. set-top boxes, video players, game consoles, audio Hi-Fi and PSU, have rated power consumption less than or equal to the 75 W harmonic limit. Accordingly, they are modelled as PE no-PFC. Game consoles are similar to set-top boxes but with higher power consumption, between 19-197 W in operating mode depending on the console, therefore they are required to include some form of PFC circuit. Based on their high energy efficient operation, it is assumed that they are equipped with a-PFC.

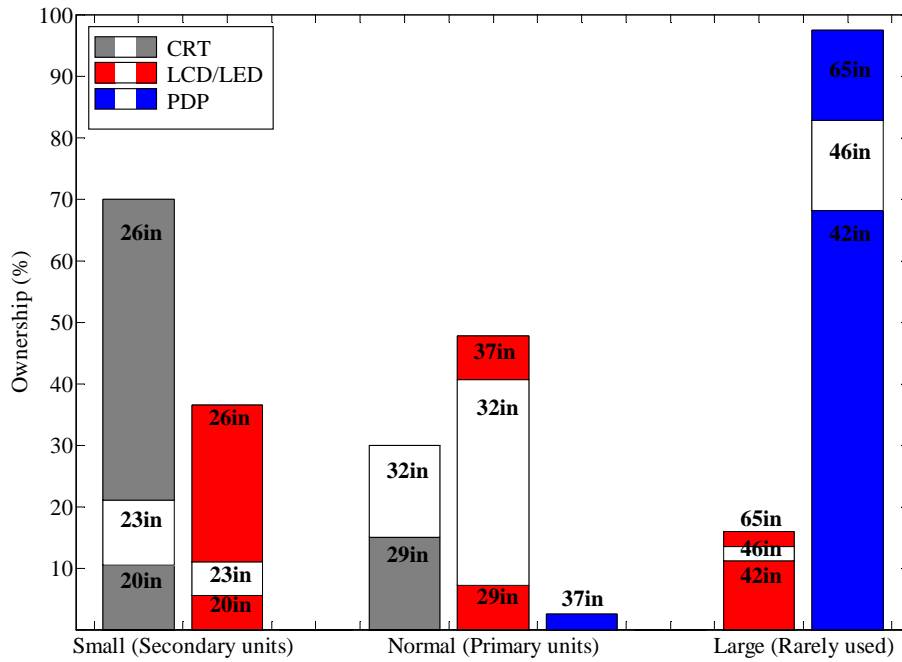
*TVs* In load use statistics, TVs are often referred to as primary and secondary. Primary TVs refer to the main use TV, while secondary TVs include smaller, lower rated power TVs with lower use frequency. Currently, there are four main variants of TV technology: cathode ray tube (CRT), liquid-crystal-display (LCD)/light-emitting diode (LED) display, plasma televisions and rear projectors (RP). The market share of the RP technology is negligible and is excluded from further analysis.

The rated power of the device will determine the electrical characteristics of the load, as a result of the implementation of harmonic legislation. All secondary appliances are considered as PE no-PFC, due to the lower rated power. For primary appliances, it is assumed that the modern appliances, i.e. LCD/LED, will utilise PE a-PFC technology, while older technologies,

i.e. CRT and plasma, will include PE p-PFC circuits to satisfy harmonic legislation. The rated power of each of these appliances varies according to the size of screen and technology and can be selected from the rated power distribution, shown in Figure 3.12.

The distribution of rated power of the LCD/LED and Plasma TV technology is best represented by the Inverse Gaussian distribution, which is defined by two parameters:  $\mu$  the mean value and shape factor  $\lambda$  (3.2):

$$f(x|\mu, \lambda) = \sqrt{\frac{\lambda}{2\pi x^3}} e^{\left\{ -\frac{\lambda}{2\mu^2 x} (x - \mu)^2 \right\}} \quad \text{for } x > 0 \quad (3.2)$$



**Figure 3.12:** TV ownership per screensize and technology[1].

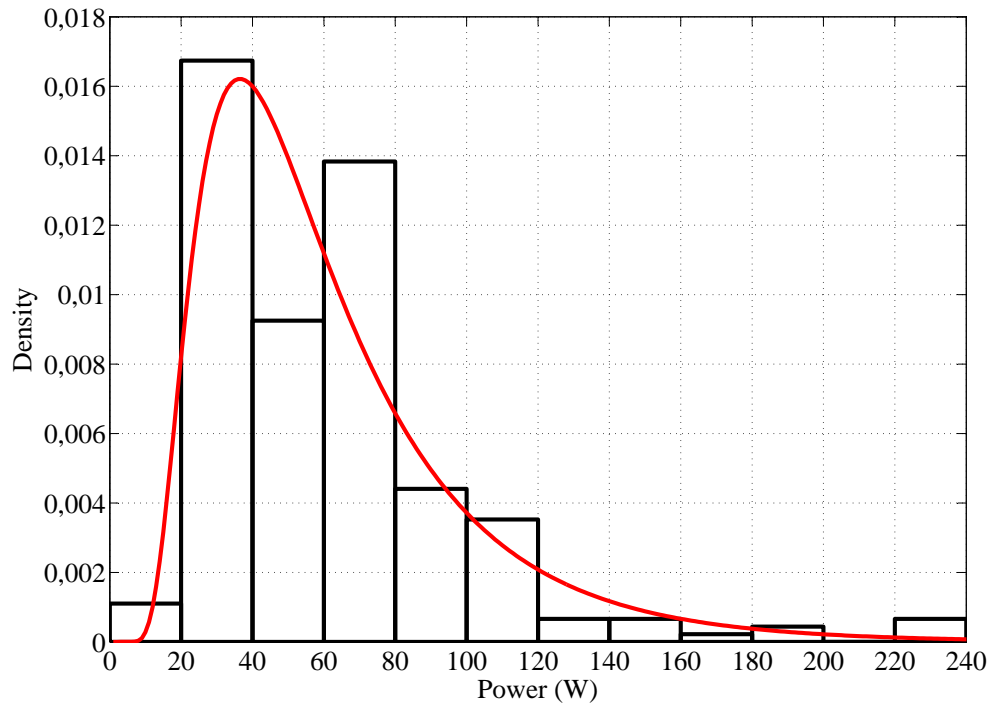
#### Ownership statistics

*Low-power and supplementary devices* As it is reported in [107], a high proportion of UK households have set-top boxes and video-players, 93% and 88% respectively. The large penetration of set-top boxes can be attributed to the growing use of digital television receivers. The ownership of audio appliances can be assumed to be a similar magnitude, around 90%. Recent statistics indicate that approximately 44% of UK households own a game console [108].

*TVs* Almost all households are equipped with at least 1 TV, with the ownership to be about 97% of households [1]. A general rule of thumb is that households do not have more than 1 appliance per occupant. Figure 3.12 was generated by combining data from reports [1, 103, 109] and the availability in the market checking hundreds appliances. It shows the distribution

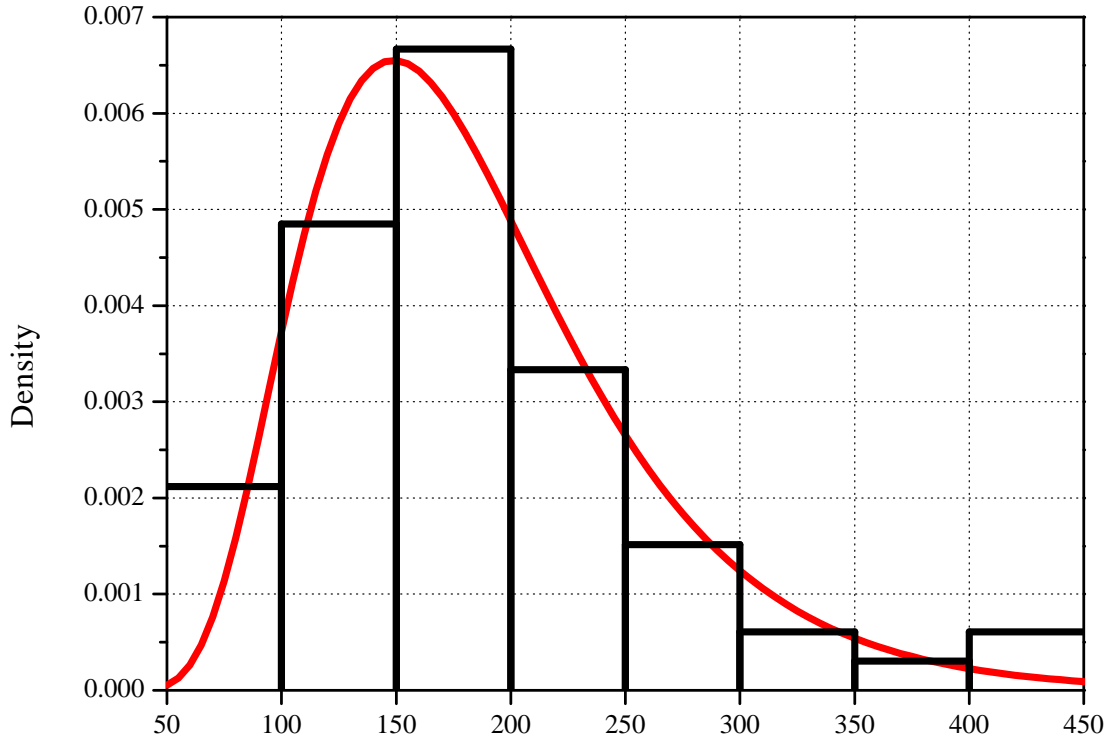
of TV ownership per screensize and use while they sum up to 100% per technology. These percentages can be scaled by the ownership per technology as they are shown in Appendix A.6. Furthermore, it can be seen that secondary and most of the primary devices are LCD and, especially, CRT TVs which are the categories that concentrate the largest market share. Large screensize TVs consist of mostly plasma TVs and projectors and a few LCDs. This distribution has a significant effect on the total power consumption of this load category.

The distribution curves of rated power, such as those presented in Figures 3.13 and 3.14, and the equivalent equations, are retrofits (the red curves) based on data (the bars) from the appliances datasheets from the manufacturers. They were selected by assessing the matching factor given by Matlab retrofit function in order to optimise the representation of the real data in the model. During the random selection of the appliances, as long as they exist, their rated power is selected based on these distributions.



**Figure 3.13:** The distribution curve of rated power for LCD/LED





**Figure 3.14:** The distribution curve of rated power for Plasma TVs

#### 3.4.1.4 Information and Communication Technology

Information and communication technology (ICT) load includes the following devices: PCs, monitors, laptops, printers and multi-function devices (MFDs). By annual power consumption, the main loads are PCs and laptops. All associated equipment will be operated in conjunction with one of these appliances.

##### *Technical description*

As with the consumer electronics load type, the required operation of all ICT devices is identical, as all appliances will include a SMPS to convert the ac supply voltage to the required dc voltage.

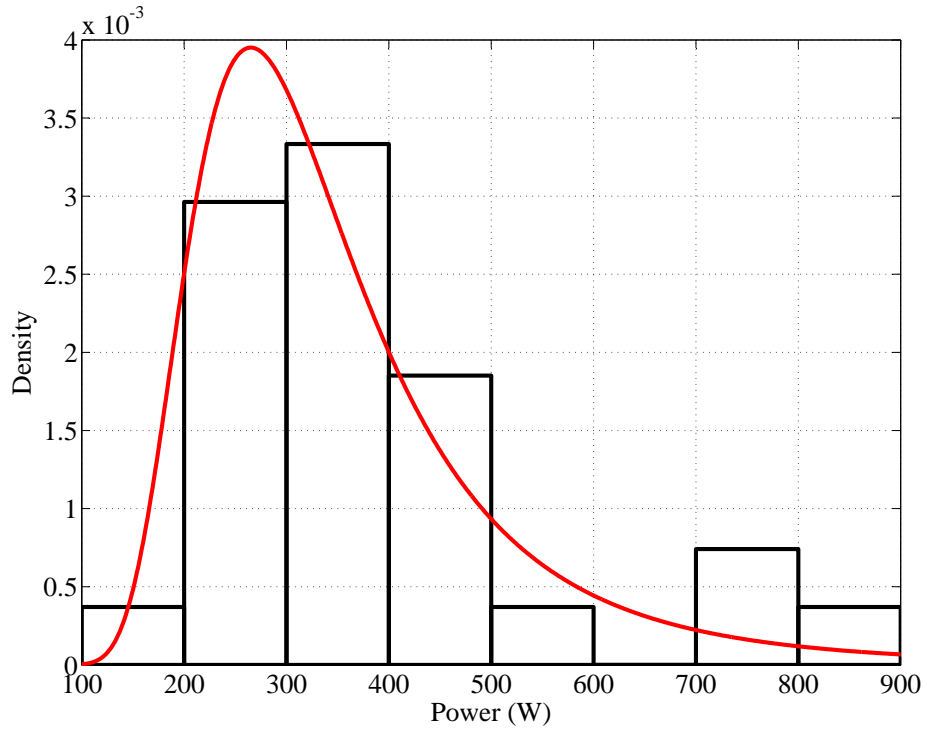
*Desktop computers* Desktops are electronic devices that are assumed to have either passive PFC or active PFC depending on the circuit of the voltage supply. The active power consumption will vary in the range 20-60% of the rated power during normal operating conditions, based on the specific operations being performed by the machine [110]. Although it is possible for the power demand to reach up to 100% of the rated value, it is not expected to last for a significant period of time. According to manufacturers' datasheets, the rated power of the voltage supply varies between 100 to 900 W and the pdf can be described by the Generalised Extreme Value (GEV) distribution (Figure 3.15). The GEV distribution is defined by three variables: the shape

parameter  $k$ , the location parameter  $\mu$  and the scale parameter  $\sigma$  (3.3):

$$f(x) = \begin{cases} \frac{1}{\sigma} \left( - (1 + kz)^{-\frac{1}{k}} \right) (1 + kz)^{-1 - \frac{1}{k}} & k \neq 0 \\ \frac{1}{\sigma} \exp(-z - \exp(-z)) & k = 0 \end{cases} \quad (3.3)$$

where

$$z = \frac{x - \mu}{\sigma} \quad \text{for } x > 0$$



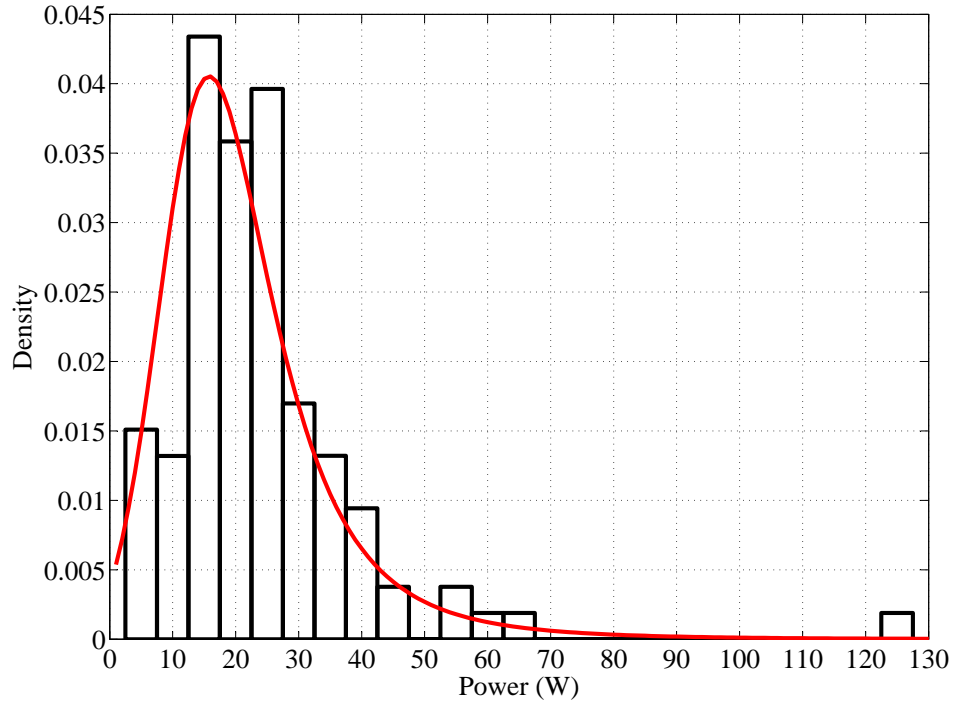
**Figure 3.15:** Rated power distribution for desktops.

**Monitors** The electrical characteristics of PC monitors are similar to TVs but due to lower power demand, they are mainly modelled as  $SMPS_{noPFC}$  for less than 75 W and  $SMPS_{pPFC}$  for those that require more than 75 W. The required power depends on the age of the device, the technology utilised and the screen size.

A typical CRT monitor will have active power rating in the range 60 - 85 W, drawing 2-5 W when in stand-by mode, based on their age. The power distribution of LCD/LED monitors can be described by the Log-Logistic distribution (eq.3.4). This distribution is defined by three parameters: location parameter  $\mu$  and scale parameters  $\alpha$  and  $\sigma$ . The fitting to manufacturers' data is presented in Figure 3.16). LCD/LED monitor stand-by consumption is similar to CRT

technology, 2-5 W [109, 110, 111].

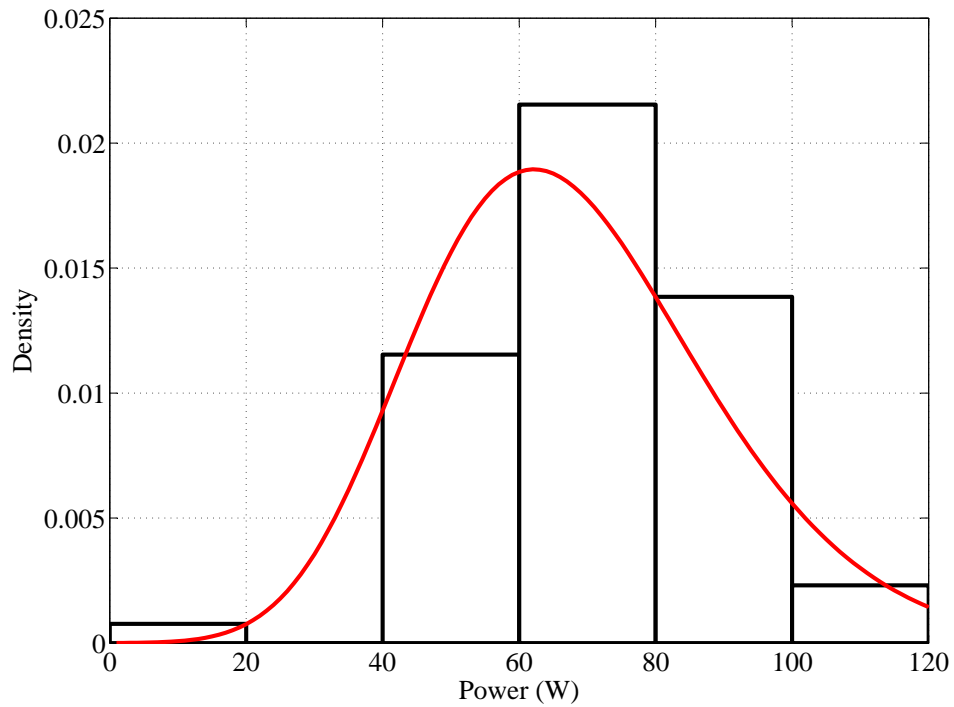
$$f(x) = \frac{\alpha}{\sigma} \frac{\left(\frac{x-\mu}{\sigma}\right)^{\alpha-1}}{\left(1 + \left(\frac{x-\mu}{\sigma}\right)^{\alpha}\right)^2} \quad \text{for } x > 0 \quad (3.4)$$



**Figure 3.16:** LCD/LED PC monitors power distribution.

*Laptops* From a number of measurements performed on laptop battery chargers, with age ranging from one to six years old, it was found that the predominant technology was PE no-PFC ( 56%), with PE p-PFC contributing 19% and PE a-PFC 25% to this load type consumption. During operation, the power drawn by the laptop will vary between 40% - 85% of the rated power charger during normal operating conditions. The distribution of power drawn by the measured laptops and the laptops that are available in the market is shown in Figure 3.17. This distribution can be represented by the GEV distribution.

*Office equipment* This is classified as printers, scanners and MFD and there are several technological variations for each appliance type. However, from a load modelling viewpoint, this will only change the rated power of the device. From [111, 112] and manufacturers' datasheets, for ink-jet printers, the rated power will lie between 10-42 W, with 2-12W in stand-by mode. The power demand of laser printers is higher, typically between 315-440 W when



**Figure 3.17:** Power distribution for laptops.

active and 5-12 W in stand-by model. The active power demand of scanners is generally around 150 W, while MFDs will range from 15 - 500 W, depending on the size of the device.

It is assumed that all devices of rated power will utilise PE no-PFC technology, with passive-PFC being the main technology in devices of higher rated powers.

*Communication appliances* Landline phones and routers are of low rated power, 7 - 30 W and are modelled as PE no-PFC [110].

#### *Ownership statistics*

41% of houses have a desktop and 78% of them have laptops in UK, while about 30% own both [1, 107]. It is assumed that there is a maximum of one desktop in each household, with a maximum of one laptop per occupant. It is assumed that only 5% of monitors currently in use are CRT technology, with the majority being LCD monitors.

Available statistics indicate that MFD are more widely used than standalone printers and scanners, with ownership approximately 57% and 33%, respectively. Router ownership is calculated in [113] and confirmed by [107], with approximately 84% of households owning a router.

### 3.4.1.5 Cooking

Cooking loads can be divided into five general types: ovens, hobs, kettles, microwaves and small appliances. In the UK, the primary energy source for the major cooking loads, i.e. ovens and hobs, is gas, which is responsible for around 57% of cooking energy. However, due to the high rated power of electric cooking appliances, there is still a considerable demand from electric cooking in the residential load sector. Recent statistics estimate that around 25% of the daily power consumption comes from cooking [114].

#### *Technical description*

Cooking includes a large number of appliances that can be used for food preparation. The main electrical cooking devices are usually resistive loads which include ohmic heating element, and their rated power consumption depends on the type of appliance and their duty cycle ( $D$ ). It is estimated that electrical hobs operate with  $D = 0.33$  for 0.75 min cycle, the values of  $D = 0.5$  for 5 min operation cycle for electric ovens are slight higher due to the higher temperatures required [101]. The intervals power demand are defined as follows: kettle [2, 3] kW and microwave [0.6, 1.2] kW, with device duration selected from a uniform distribution between [2, 5] mins. For electric ovens, the power demand will vary based on the device duty cycle  $D = 0.5$  (5 min cycle) within typical power ranges [0, 2] kW, with device duration selected from a uniform distribution between [30, 90] mins.

The more complex operation of microwaves requires the rectification of the supply voltage and is modelled as PE p-PFC, while food processors are modelled as  $CSCR_{CT}$  motors. Reports, e.g. [1, 31, 103, 112, 115, 116], and manufactures' data give typical power range of the devices in market with a summary presented in Table A.8.

#### *Ownership statistics*

More than half of UK households (62%) are equipped with electric ovens, while less than half (46%) have electric hobs [31, 101, 103]. Microwave ovens are more frequently found in UK dwellings, and the ownership is reported to be about 92% [1]. The penetration of smaller appliances, i.e. kettle, a toaster or a food processor, is considered to include all UK households [1]. Table A.8 presents the ownership statistics and the rated power ranges, given as uniform distribution.

#### 3.4.1.6 Shower

Similar to the cooking activity, it is possible to use electrical showers, which are essentially instantaneous water heaters (see Section 11), or to draw hot water from a gas boiler system.

##### *Technical description*

The water is heated up instantly by a heating element with high rated power that may vary between 4 to 9 kW [103]. It is assumed that the power consumption remains constant during the activity since there is not any tank to store the hot water and new, cold water is constantly drawn into the appliance. The electric shower is modelled as a constant resistance load due to the use of resistive heating element.

##### *Ownership statistics*

It is estimated that about 49% of UK households use electricity to heat the water and 90-92% of them are equipped with electric showers [101, 117].

#### 3.4.1.7 Miscellaneous loads

This load type covers all small devices that either have low power consumption or have low frequency of use. In this report, this includes: vacuum cleaners, irons and hairdryers. These appliances usually have high rated power but they are used less frequently and for short periods of time.

##### *Technical description*

Vacuum cleaners consist of a  $CSCR_{CT}$  motor because of the high running torque that is required. An iron is mainly a large resistive heating element while a hairdryer model is a combination of both. Hairdryers consist of a high running torque motor and a resistive element to heat the air. A summary of manufacturers' data is presented in Table A.9.

##### *Ownership statistics*

The penetration of vacuum-cleaner in market is 93.7% [118]. Similarly, steam irons and hairdryers are assumed to be in the majority of households.

#### 3.4.1.8 Lighting

##### *Technical description*

GILs have an electrical filament in a glass bulb filled with inert gas that is heated to a high temperature until it glows. Halogen lamps are very similar to the GIL's. They are also made of a filament inside a glass bulb that contains halogen gas. The chemical reaction between the filament and the gas allows for higher luminous efficacy for the same amount of power in comparison with GIL. Therefore, the electrical characteristics will be similar. The fluorescent lamp is a gas-discharge lamp that uses electricity to excite mercury vapor. To initiate and control this process, a sophisticated ballast circuit is required. There are two types of fluorescent lamps according to the shape: linear (LFL) and compact (CFL). LED LS are the most technologically advanced type of lamp which consists of light-emitting diodes and an internal (or external) rectifier to supply them with direct current (DC).

Due to technological differences, each type of lamp is modelled requires a unique load model (see Table in Appendix A). Further details are provided in [50, 119].

##### *Ownership statistics*

Lighting is assumed to consume approximately 20% of the total residential power consumption [1, 120]. In 2010, CFL, halogen and GIL lamps are the three dominant types of lamps in the UK market, with market shares of each type given in Table A.10 [1, 120]. Given that GIL share is being reduced gradually over time, the share of CFL and halogen lamps will increase further in the future.

#### 3.4.1.9 Heating

The principal energy source for space heating in the UK is gas. However, some households will use resistive heating systems in conjunction with off-peak electricity tariffs. A more common form of electrical space heating is in the form of electric storage heaters and there is a small share of smaller/portable instantaneous electrical heaters.

##### *Technical description*

The rated power of electric space heating ranges between 4 to 8 kW with uniform distribution [101] and modelled as a resistive element. The storage heaters need to be charged and then they heat the room by using the stored energy. They require a lot of time to charge and, consequently, they are a large resistive load which is mainly installed in houses that have Economy 7 tariff and are charged during night.

##### *Ownership statistics*

As stated previously, gas is the dominant energy source for space heating in the UK residential load sector. However, there is a small proportion of houses, approximately 7.5%, that are equipped with electrical space heating. 75% out of them have installed storage heating systems and only 25% is using instantaneous electrical heaters [1].

### 3.4.2 Power demand profile

This section describes the conversion of user activities profiles into electrical power demand profiles. The proposed conversion approach divides the calculation process into two different procedures depending on the following two types of loads:

- The operation of which directly affects the electrical profile
- The operation of which depends on various environmental factors such as solar irradiance and temperature

The conversion of user activities (Table 3.1) into power demand depends on the nature of the activity. In order to calculate the power demand of the household, the majority of activities of each occupant are connected with at least one appliance  $a$  from the appliances database (Table 3.2). The conversion is relatively simple and includes mainly the device ownership  $O_a$  and statistical distributions of operating power. However, there are activities that require more information related to the use and purpose of the appliances connected to them, such as time of use statistics. The general form of conversion process can be described by (3.5). The user activity state  $U_i$  at time  $t$  is combined with  $O_a$  and probabilistic functions  $T_{i,a}$  of use of electrical appliance  $a$  associated with user activity  $i$  to convert to a power demand profile for appliance  $P_a$ .

$$P_a(t) = (U_i(t) \cap O_a \cap T_{i,a}(t))X \quad \forall a \quad (3.5)$$

where:  $X$  is a random value for power of appliance  $a$  (in watts), with a probability distribution  $f_{P_a}(x)$  as described in [7].

The device use duration depends on the nature of the device. For some appliances, their operation is defined by the duration of the activity, such as the majority of ICT/CE. For devices like wet loads, the use duration is set according to typical appliance use profiles. As it is stated in Section 3.3, the resolution of the user activities time series is 10 minutes which is an issue for the appliances that operate for less than 10 minutes. The proper representation of such loads and the need of providing power consumption time series of higher resolution require conversion into smaller simulation time step of 1 minute.

The total household demand is obtained by summing the demand of all household appliances:

$$P_{hh}(t) = \sum_{a=1}^A P_a(t) \quad \forall t \quad (3.6)$$



$$Q_{1,hh}(t) = \sum_{a=1}^A P_a(t) \tan(\cos^{-1}(PF_{1_a})) \quad \forall t \quad (3.7)$$

where:  $P_{hh}$  and  $Q_{1,hh}$  are the household active and (fundamental) reactive power demand,  $P_a$  and  $PF_{1_a}$  is the active power demand and displacement power factor respectively of appliance  $a$  and  $A$  is the total number of appliances.

**Table 3.2:** Allocated appliances for each user activity

id.	User activities	Allocated appliances
1	Non-electrical activity in home	No appliance is required
2	Sleeping	No appliance is required
3	Wash/Dress	Electrical shower
4	Food preparation	Electric oven Electric hob Microwave oven Food processor
5	Dishwashing	Dishwasher
6	Cleaning house	Vacuum cleaner
7	Laundry	Washing machine Tumble dryer Washing dryer
8	Ironing	Electric iron
9	Computing	Desktop Monitor Printer Laptop Game consoles
10	Watching TV	TV Set-top box
11	Watching video/DVD	DVD player (& TV)
12	Listening to music/radio	Radio
13	Out of house	No appliance is required

However, there are some variations among the load categories on the implementation of the conversion process. These differences exist primarily due to their usage and occupants' lifestyle. This feature makes the tool location-dependent since it is possible to model populations with demographical characteristics corresponding to real geographical locations.

According to the nature and use of residential appliances, there are five types of conversion algorithm:

- Type 1: loads that are unrelated to user's activities,
- Type 2: loads that are fully dependent on user's activities,
- Type 3: loads that do not depend on user's activities completely,
- Type 4: activities that correspond to more than one appliance but is not necessary that all of them are used,

- Type 5: loads that are dependent of environmental conditions.

It is possible that appliances belong to more than one type because of their characteristics. Then, the conversion algorithm is a combination of the corresponding types.

#### **3.4.2.1 Type 1**

Some domestic appliances are not connected to any activity. These appliances operate for a large period of day, usually the whole day, by consuming a fixed amount of energy. These devices operate either periodically, such as cold loads, or the power demand is constant such as phones and routers.

#### **3.4.2.2 Type 2**

The CE/ICT (except phone and router) loads and those that are used for housework belong to this type. For these loads, the conversion process is followed as it has been described. However, in the case of CE/ICT, an additional parameter is involved in calculating the power demand, the stand-by mode feature. In order to include that in the model, the classification of the user's behaviour is needed (see Section 3.3).

#### **3.4.2.3 Type 3**

This type describes the activities that are not directly converted into power demand, since more factors should be taken into account. One of these factors is the duration of the operation cycle of the appliances where the activity is considered as the indicator of the starting point, such as wet loads. For example, the "laundry" activity is translated as the loading of the washing machine. After that though, the duration of the washing machine is much longer than the 10min time step of the activity profile.

Furthermore, some activities are not always converted into power demand as there is the possibility of manual completing of the activity. Appliances that belong to this type are washing machines, dishwashers and electric showers.

Another factor of the conversion is the seasonality of the use of a load. Wet loads are an example of this case and the tumble-dryer in particular. In a lot of countries where the changes of weather conditions are radical between the seasons, a variation in the probability of using the appliance is noted.

## 3.4.2.4 Type 4

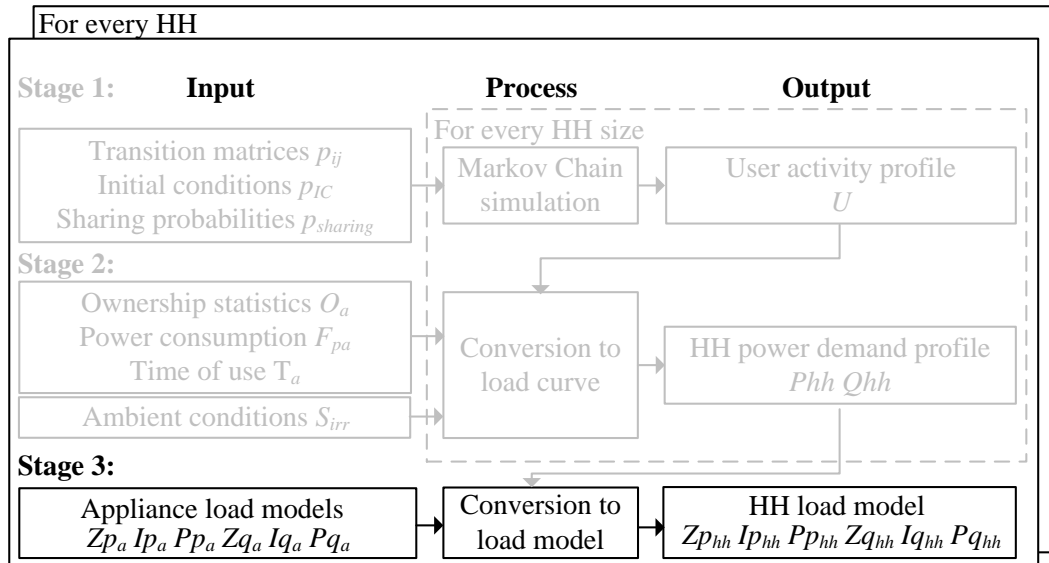
The modelling of "cooking" activity requires different approach due to the number of appliances that is connected with as not all of them are used at each occurrence of the activity. The selection of the cooking appliance(s) depends on the use statistics for each appliance.

## 3.4.2.5 Type 5

Lighting is a typical example of loads driven by the weather conditions, global solar irradiance in this case. Although the presence of occupants is necessary in the dwelling, the required power demand depends on the level of illumination inside the house. The physically based lighting model is based on the model developed in [121] and it has been altered accordingly to be integrated with the developed tool.

## 3.5 Stage 3: Electrical load model

The last stage of the tool includes the development of the load model of the household. The tool is capable of using two of the most popular forms of illustrating the temporal variations in load characteristics of loads,



**Figure 3.18:** Work flow of stage 3.

The aggregated load model of the household is the combination of the individual load models. Each appliance is modelled by one or more components according to their nature. For instance, appliances with operating cycles (e.g. dishwashers, washing machines and tumble dryers) are

modelled according to the function that is being done at each time step. At any time step, the load models of the individual appliances that are used are aggregated to produce a load model for the entire household using a weighted summation, given by (3.8) and (3.9) respectively.

$$\begin{bmatrix} Z_{p_{hh}} \\ I_{p_{hh}} \\ P_{p_{hh}} \end{bmatrix} = \sum_{a=1}^A \frac{P_a}{P_{hh}} \begin{bmatrix} Z_{p_a} \\ I_{p_a} \\ P_{p_a} \end{bmatrix} \quad (3.8)$$

$$\begin{bmatrix} Z_{q_{hh}} \\ I_{q_{hh}} \\ P_{q_{hh}} \end{bmatrix} = \sum_{a=1}^A \tan(\cos^{-1}(PF_{1_a})) \frac{P_a}{P_{hh}} \begin{bmatrix} Z_{q_a} \\ I_{q_a} \\ P_{q_a} \end{bmatrix} \quad (3.9)$$

where:  $Z_{p_{hh}}$ ,  $I_{p_{hh}}$ ,  $P_{p_{hh}}$ ,  $Z_{q_{hh}}$ ,  $I_{q_{hh}}$  and  $P_{q_{hh}}$  are the real and reactive components of the aggregate household ZIP model respectively,  $A$  is the total number of household appliances,  $a$  is the appliance index,  $P_a$  is the power demand of appliance  $a$ ,  $P_{hh}$  is the total household power demand,  $Z_{p_a}$ ,  $I_{p_a}$ ,  $P_{p_a}$ ,  $Z_{q_a}$ ,  $I_{q_a}$ ,  $P_{q_a}$  and  $PF_{1_a}$  are the real and reactive ZIP model components and displacement power factor of appliance  $a$ .

### 3.6 Examples of the conversion tool

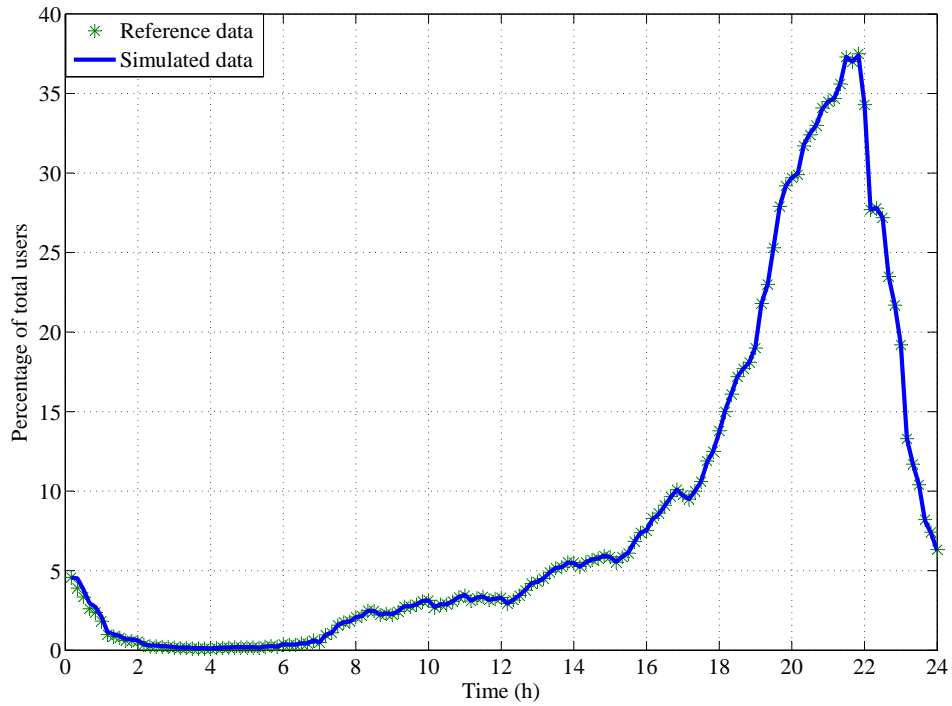
Although the first type of conversion algorithm is straightforward and unrelated to the users' activities, the remaining four are more complicated. For better understanding of the process, one representative case of each of the four types of the conversion algorithm has been selected to be used as examples to describe all stages.

For the second type of conversion algorithm, the 'watching TV' activity is used as an example. 'Laundry' and 'cooking' are perfect examples of activities that are converted into power demand to describe the third and fourth type of conversion algorithm respectively. The calculation of the power demand of lighting is used to describe the operation of the last type of algorithm.

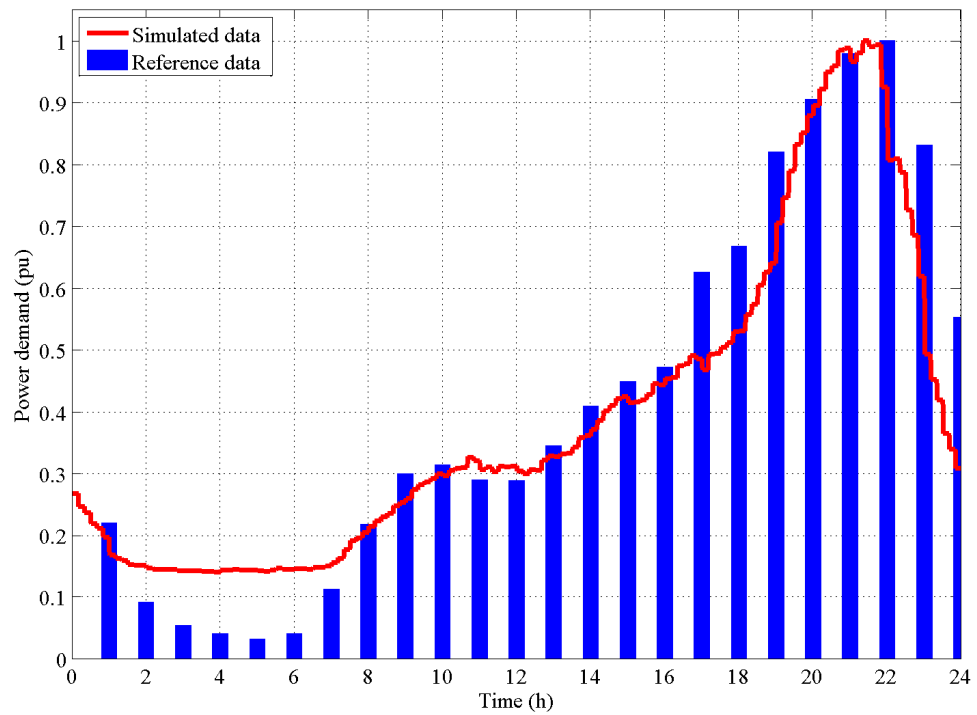
#### 3.6.1 Watching TV

Watching TV belongs to the activities that are directly converted into power demand. However, there is one more feature that affects the daily power demand and has to do with the customers' trend in using the stand-by mode of the appliance, see Sec. 3.3. The power demand in both modes depends on the size, type and model of TV [6].

Figure 3.19 shows the result from stage 1 of the model. The simulated data of the users that watch TV at each time step of the day are compared against the measured data that have been reported to the TUS UK by the participants. This explains the exact match of the two datasets and proves at the same time the proper function of the model.



**Figure 3.19:** Generated activities profiles of watching TV compared to the data from TUS UK.



**Figure 3.20:** Conversion of watching TV into active power demand compared with data from [1].

### 3.6.2 Laundry

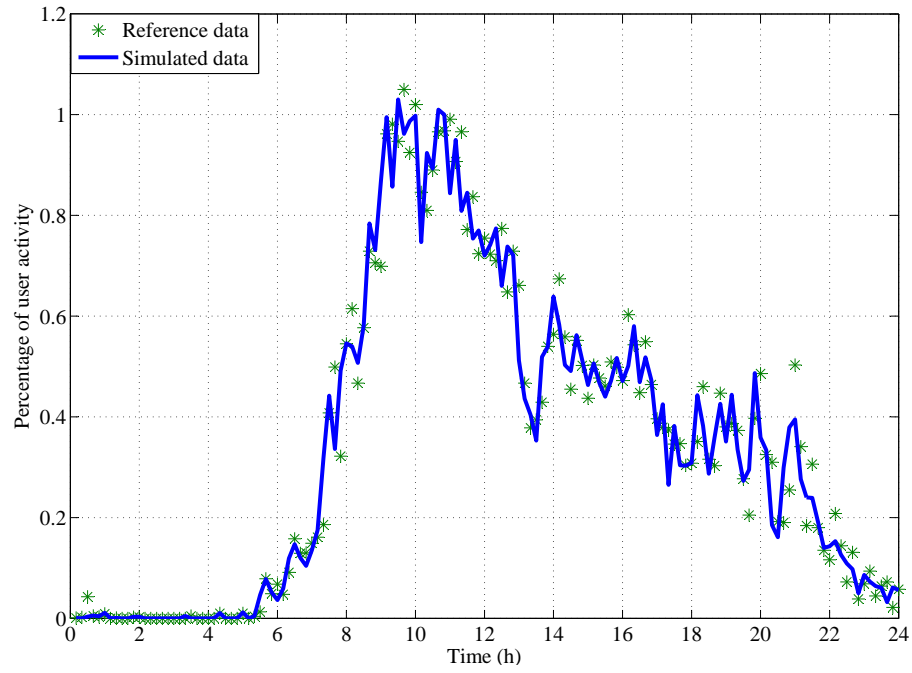
The 'laundry' activity requires use of electricity, as it is assigned to the use of washing machine, provided that the household is equipped with such an appliance. However, there is a possibility that the activity is performed either by hand or not at home and also the fact that the 'laundry' activity includes more actions than starting the washing operation, e.g. loading or unloading the washing machine. This explains the difference between the two datasets in Figure 3.21 and sets the different approach of modelling this load from TVs. Therefore, the probability of using dishwasher for each time period of the day should be consider to define which activity occurrences do not require the appliance (Figure 3.22).

Some assumptions have been made at this point to convert the activity into power demand. Based on the fact that, on average, washing machines are used 5 times/week [105], it is assumed that they are used maximum once per day (Figure 3.21). Furthermore, if the laundry activity occurs once during the day, it is assumed that the washing machine is used to perform it and thus it is converted into an electrical activity. In case that more than one occurrence is noticed then the most likely event is being converted into an electrical activity. To do this, a random number  $[0,1]$  is selected to define one of the time periods of the day. If there is an event during this time period, then it is converted into an electrical activity (Figure 3.22). To adjust the operation of the appliance to the resolution of the power demand time series, a random integer between  $[0,9]$  is selected in order to define the start time point of the operation of the washing machine. The length of the operation cycle and the power demand of each stage of the cycle are defined as described in [6]. Finally, the power demand for the whole operation cycle of the device is added to the power time series (Figure 3.23).

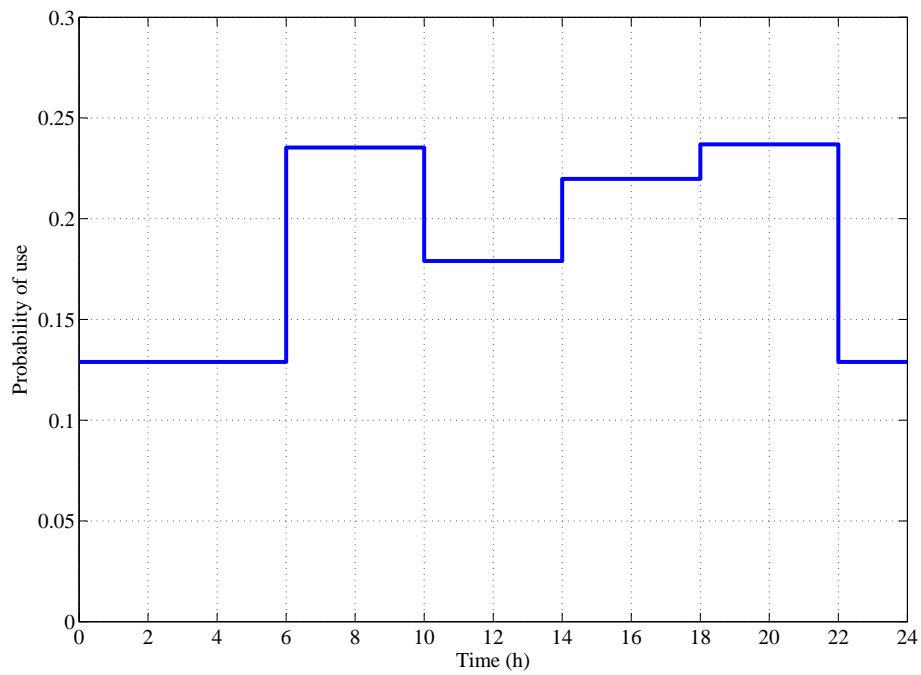
### 3.6.3 Cooking

The conversion of 'cooking' activity into power demand is presented in this section as an example. Figure 3.24 illustrates the percentage of users that are involved with the 'cooking' activity during the day. The discrete probability functions of appliance use  $A_{ij}$  in the UK are shown in Figure 3.25. For kettles and microwaves, the power demand is assumed constant during operation and selected from a uniform distribution.

After selecting the used appliances according to Figure 3.25 for each occurrence of the 'cooking' activity, the activities are replaced by the power demand of the appliances forming the curve in Figure 3.26. The fitting values for the cooking consumption are  $\sigma_{XY} = 0.96$  and  $RMSE = 0.08$ , which indicates that the developed model is able to reproduce the expected demand.



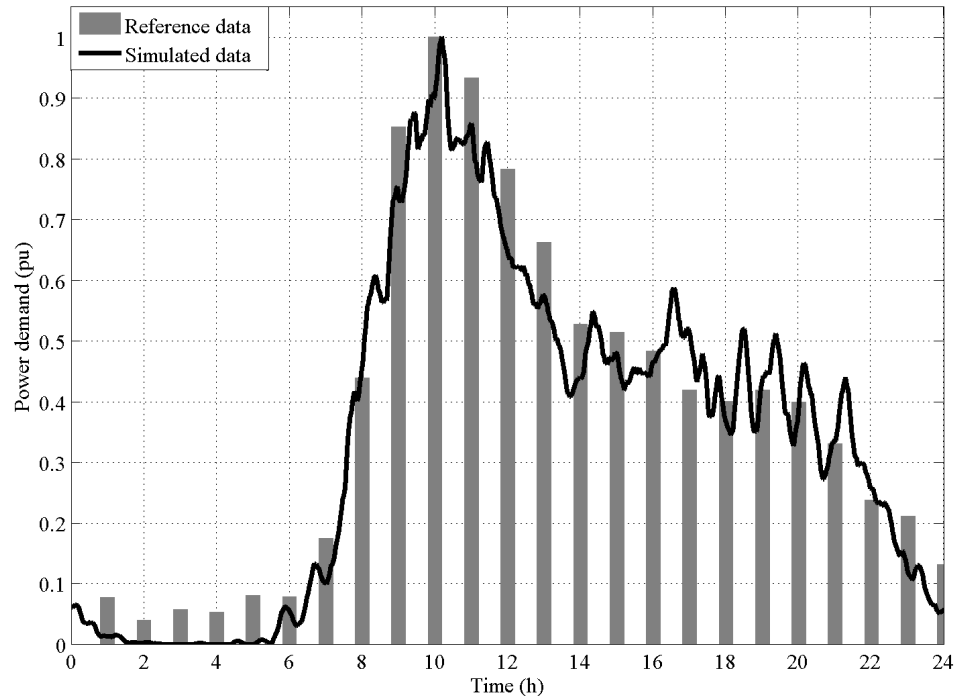
**Figure 3.21:** Activities profiles of laundry compared to the data from TUS UK.



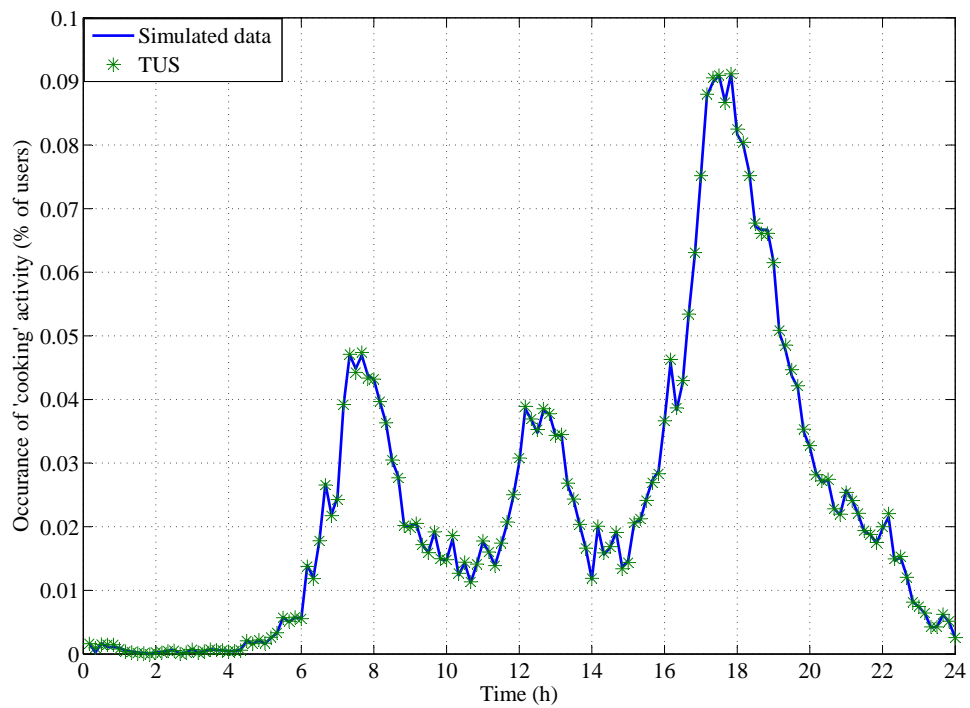
**Figure 3.22:** The probability of using the washing machine during the day.

### 3.6.4 Lighting

The possibility of turning on the lights in a room depends mainly on the available outdoor global irradiance and the occupancy. The use of domestic light varies based on the season, the



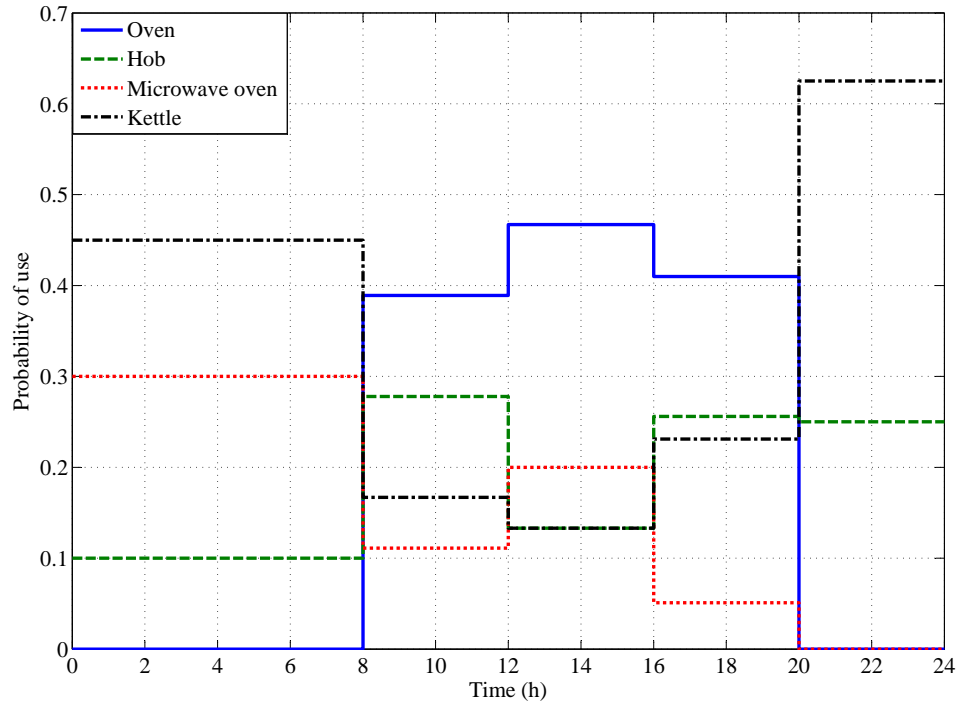
**Figure 3.23:** Conversion of the 'laundry' activity into active power demand.



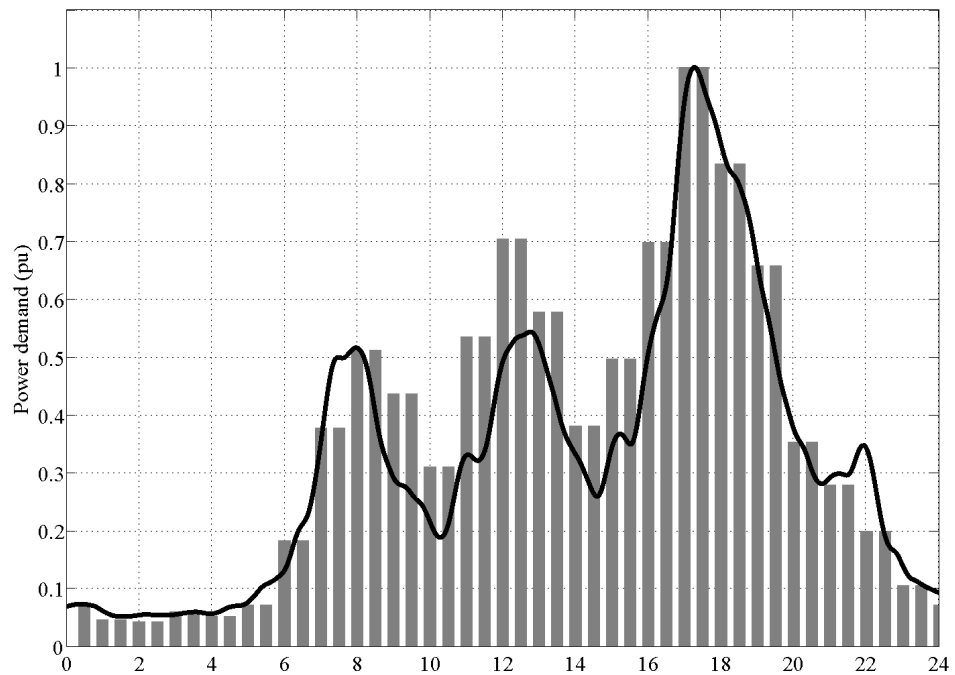
**Figure 3.24:** Activities profiles of cooking.

weather and other obstacles around the house that prevent daylight from entering the house, i.e. trees, hills, tall buildings etc. The lighting model has been developed by the Loughborough





**Figure 3.25:** The use statistics of the cooking appliances during the day.

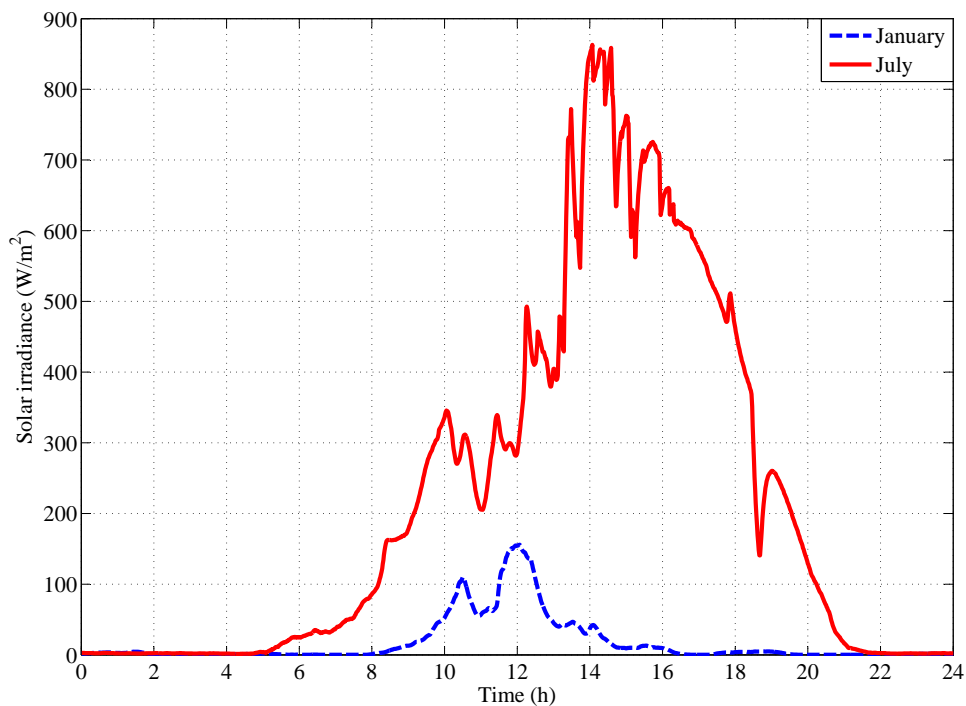


**Figure 3.26:** Conversion of the cooking activity into active power demand.

University team [121] and was integrated in the tool. Although the Matlab code is based on the Loughborough team model, some features have to be changed in order to adjust it to the

developed tool.

In the model, an average daily solar irradiance per month (Figure 3.27) is used as it has been acquired from the CREST irradiance database [98] and an irradiance threshold is defined for each house. The daylight is compared with this threshold at each time step (1 minute) to determine whether artificial light is needed. Additionally, the model provides the possibility of turning on the lights even it is not necessary (5%). Then, the occupancy profile is developed by the first stage user profile development tool (Figure 3.28). The occupancy is considered as the second important factor of switching on and off the lights. When artificial lighting is needed, the code checks the occupancy profile at each time point and if there is at least one person in the room then the possibility of turning on the lights increases. Then, the demand for artificial light is converted into power demand (Figure 3.29). Further details of the model are described in [121].



**Figure 3.27:** Average daily solar irradiance for two extreme cases, January and July.

Apart from the necessary changes in the code for the translation into Matlab and its adjustment to the tool, some features of the model were altered. One of these features is the choice of the number of installed light bulbs in each house and its power rating. In Loughborough model there are 100 specific combinations of multitude and ratings based on the statistics of the different types of light bulbs in houses from Home Lighting Audit Report of The Lighting Association. In the new version of the model, this list will be created at the beginning of the code for each house individually based on the current statistics on the mixture of residential

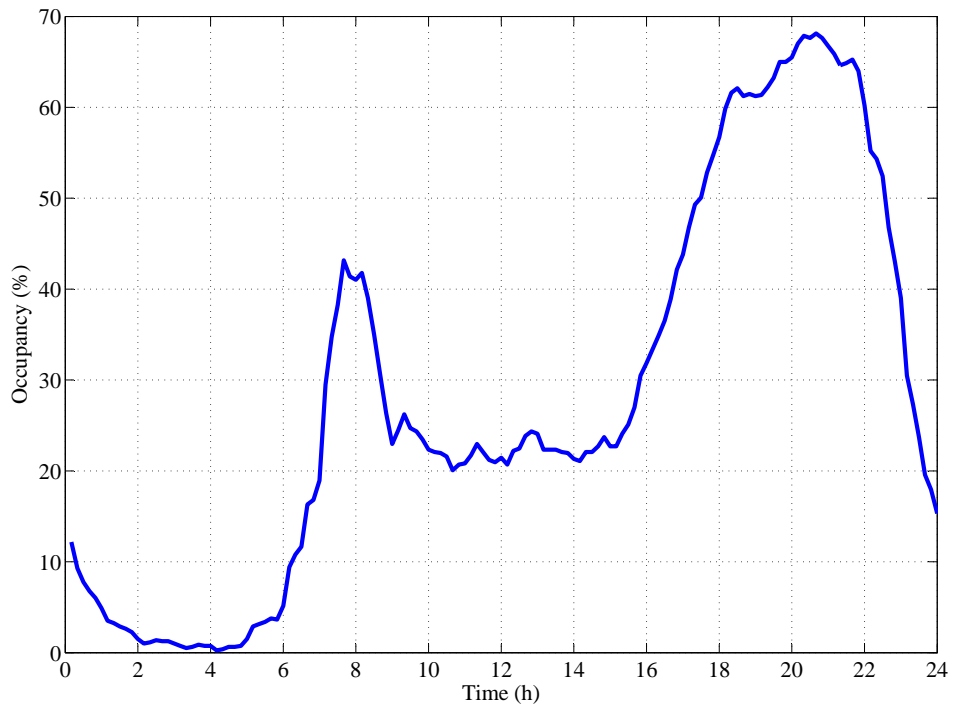


Figure 3.28: Occupancy profile.

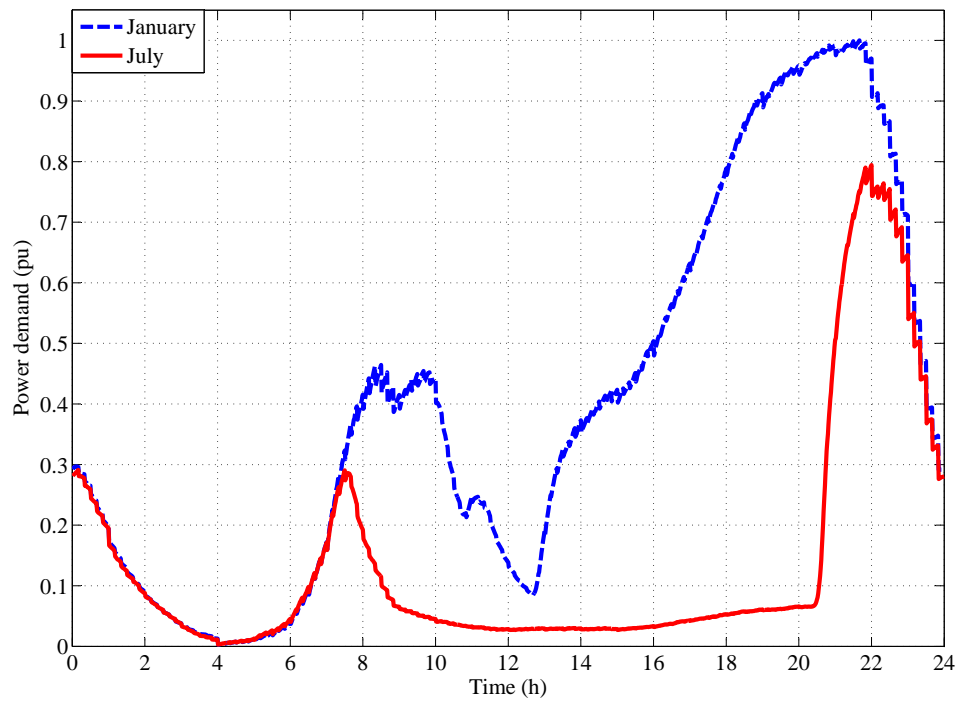


Figure 3.29: Power demand for lighting for two extreme cases, January and July.

light bulbs. The tool provides the option of changing this mixture to simulate different case studies, such as replacement of the older light bulbs.

### 3.7 Validation through UK residential load sector

The purpose of the developed tool is to represent correctly the power demand model of the residential load of a given location so as to be used in power systems studies. In order to prove the validity of the tool, the UK residential load was used as an example. A group of 10,000 households was developed to represent the UK population mixture and the required databases were formed accordingly to depict the UK lifestyle. Table 3.3 includes the demographic characteristics of the UK population regarding the size of household and the number of employed occupants, as they were described in Section 3.3, according to [122].

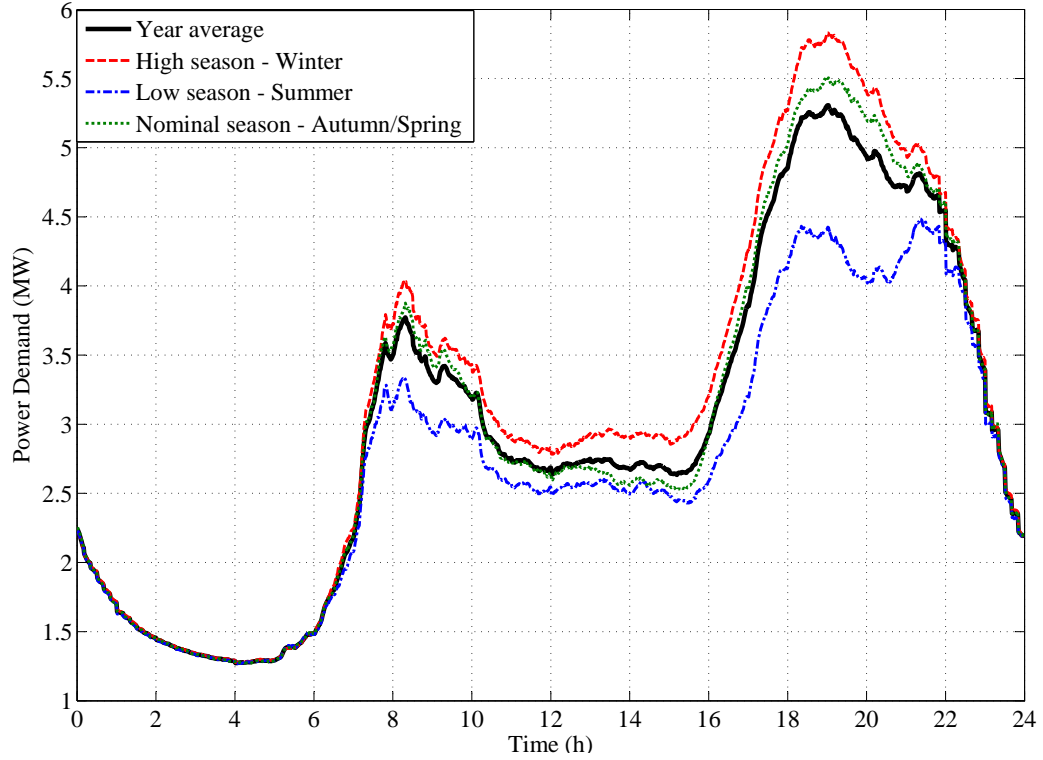
**Table 3.3:** UK population statistics as percentage [122].

HH size	Working occupants				
	0	1	2	3	4
1	12	23	-	-	-
2	3	8	23	-	-
3	1	4	11	1	-
4	1	3	8	1	1

In order to demonstrate the seasonal feature of the tool, the twelve-month period has been divided into three seasons. Winter is assumed as the season with the maximum loading conditions and includes half of October, November, December, January and February. Autumn and spring form the nominal season and are described as the season with average loading conditions. Nominal season includes March, April, half of May, September and half of October. The low season represents summer and includes half of May, June, July and August.

Figure 3.30 depicts the active power demand of the simulated 10,000 households and the difference among the various seasons and the annual average consumption. The difference between the seasons is attributed to the seasonality of certain loads. These loads are mostly lighting, cooking and wet loads.

The results of the model are verified against freely available data from official published reports. For the aggregated power demand comparison, three datasets were used. Reference dataset 1 has been published by Building Research Establishment (BRE) [123] and reference dataset 1 is from UK Energy Research Center (UKERC) [124]. Reference dataset 3 was drawn by the Department of Energy and Climate Change (DECC) [1] and provides data useful only for the annual average power consumption comparison. The variation between the reference datasets is introducing a large error margin in the calculation.

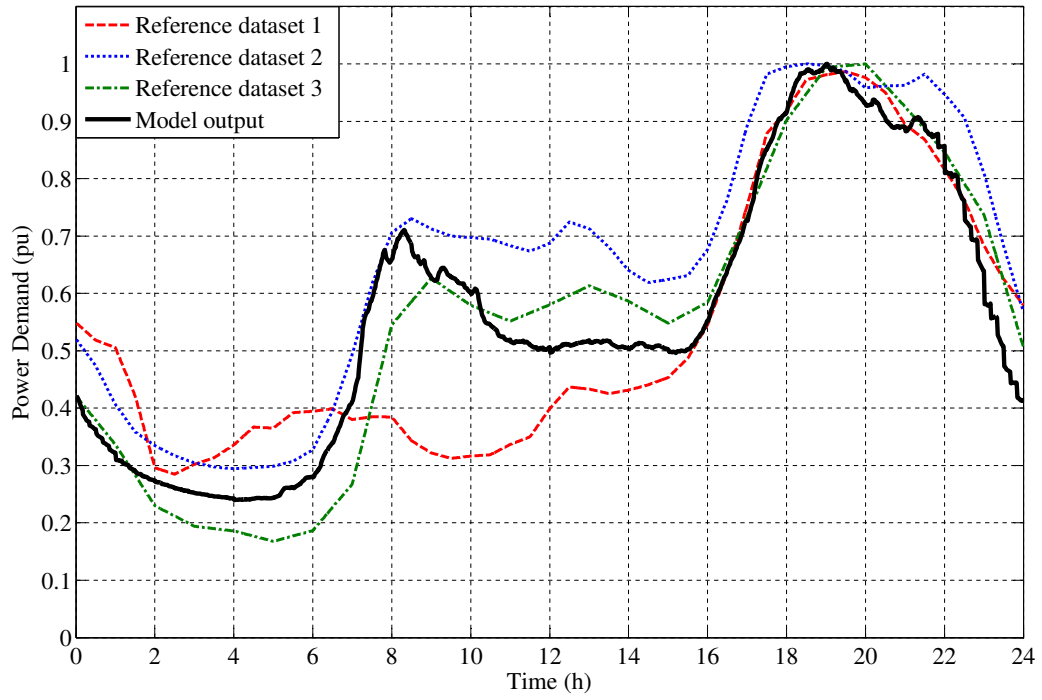


**Figure 3.30:** The active power demand of the simulated households in each season and annual average.

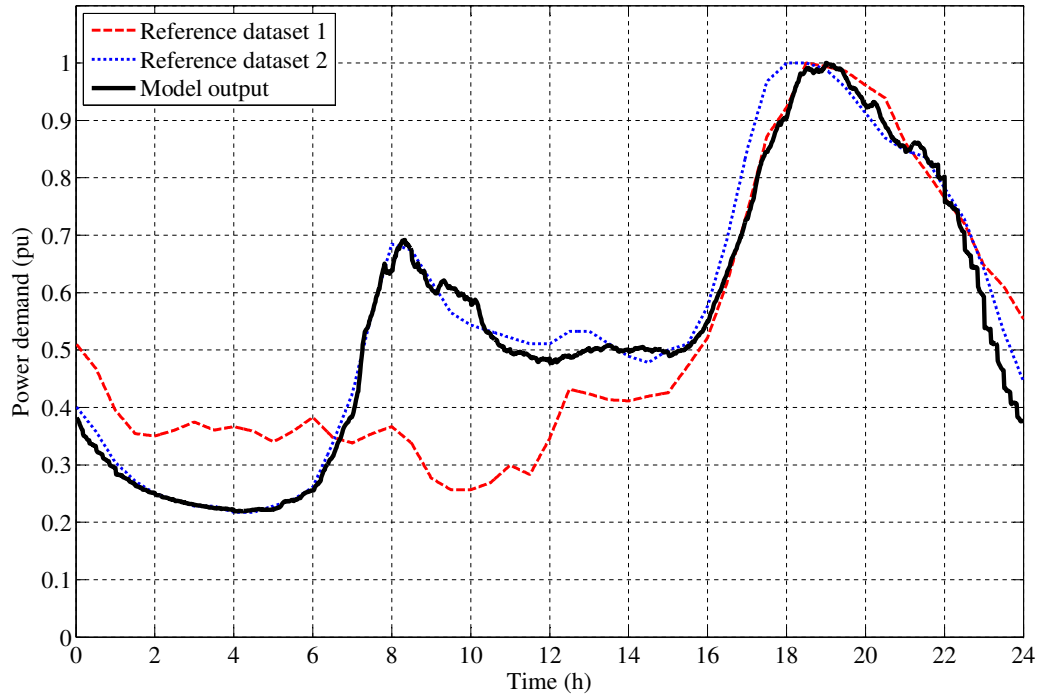
In all four figures, the modelled demand curve is between the reference curves. In Figure 3.31, the annual average of the simulated data is matching well with reference datasets 2 and 3 by following their main characteristics. The evening peak matches very well in time and magnitude with DECC curve while the morning peak matches with the UKERC curve. The plateau during night-time lies between the two reference curves. The daytime plateau seems slightly underestimated but the difference between the modelled demand and the DECC curve is not greater than that between the two reference datasets.

Similarly, the power demand of the individual seasons matches relatively well with the reference data. The greater similarity between the modelled data and reference curves occurs in high season, Figure 3.32. This happens because the available appliances use statistics refer mostly to winter as the majority of the energy systems studies are conducted for maximum loading conditions. So the settings on some loads, when no other data are available, refer to maximum loading. Furthermore, the model output is closer to the shape of reference dataset 2 as both refer to the average national energy consumption. Reference dataset 1, despite the attempt to scale up the results to a UK national level, the local characteristics of the population that was measured remain.

Regarding the nominal values of active power demand, which refer mainly to spring and autumn, Figure 3.33 shows that there is a relatively good matching with the reference datasets.



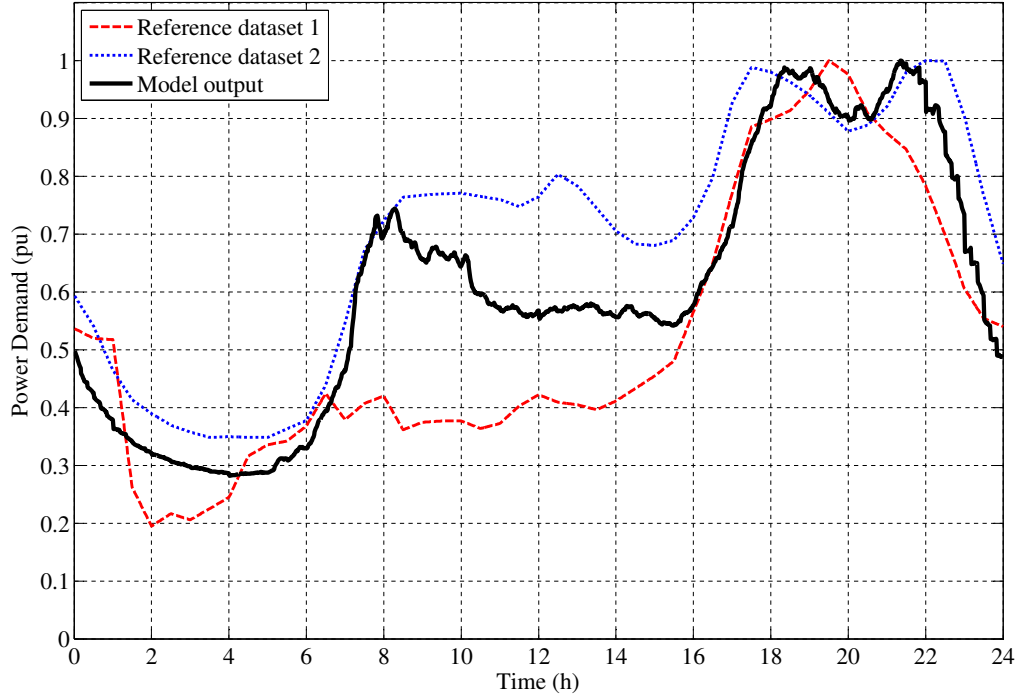
**Figure 3.31:** Annual average power demand comparison between the tool and [1, 123, 124].



**Figure 3.32:** Power demand during high season comparison between the tool and [123, 124].

The time period and the duration of the consumption during the night, the day plateau and the evening peak coincide with the reference datasets. As for the values, although there is some

difference between the model output and the reference datasets, especially during the day, the variation is between the variation that the reference values set themselves. The time that the evening peak occurs slightly differs between the model output and the references, while the reference datasets present different shape as reference 1 completely ignores the second peak. This difference evaluation of the power demand during the most important period of day from a power management point of view, shows the uncertainty of the existing datasets.

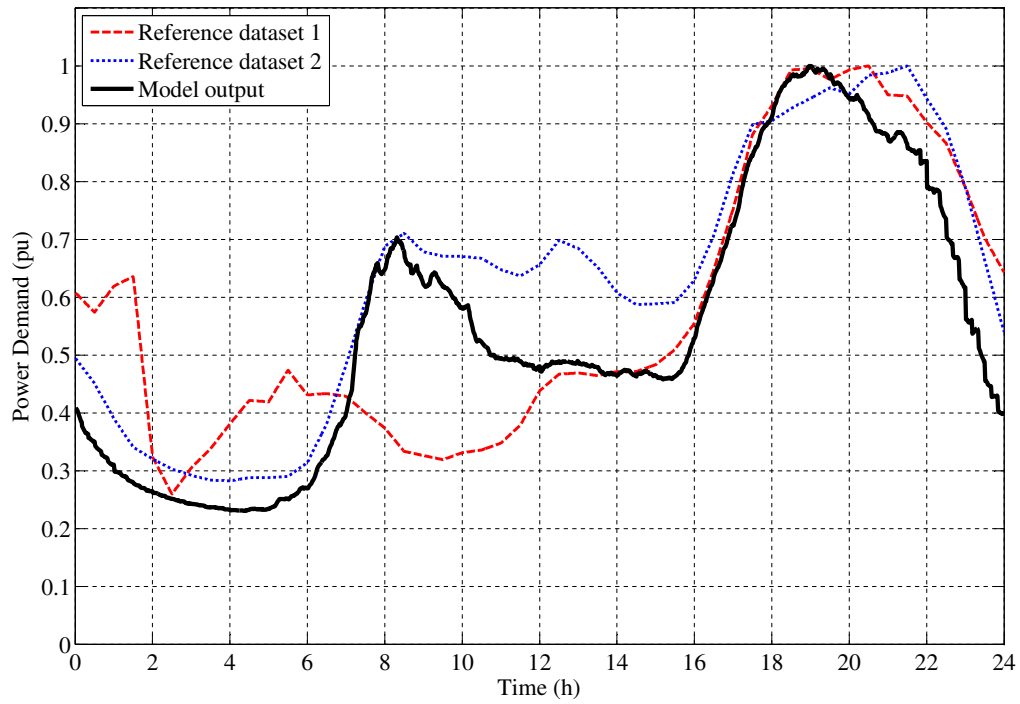


**Figure 3.33:** Power demand during nominal season comparison between the tool and [123, 124].

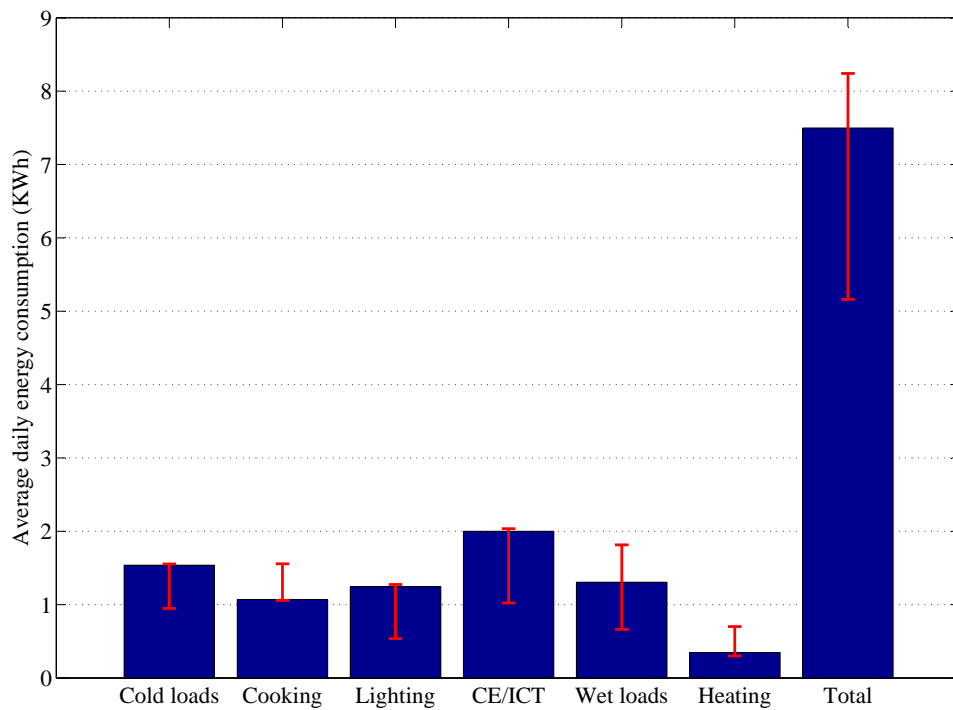
Similar results can be seen in Figure 3.34, where the model output for the average summer consumption, the low season, is compared to the two reference datasets.

The average daily energy consumption of a household in total and the contribution of each load category in that are presented in Figure 3.35. The bars define the range of the energy consumption set by literature [1, 101, 123, 124, 125]. The lack of efficient amount of data for some load categories or contradictory information about the use for some others has led the simulated energy consumption to be very close to the limits in some load categories. However, it is obvious that it does not exceed the range in any of them and the results fall within the range found in literature, which proves that the model generates not only realistic curves of power demand, but their composition is also very close to the real values.

One important feature of the tool is the seasonal diversification of the load. One example of this ability is the load from cooking category and the change of the consumed electrical energy during the year which derives from the users' lifestyle. Figure 3.36 presents this change as it is



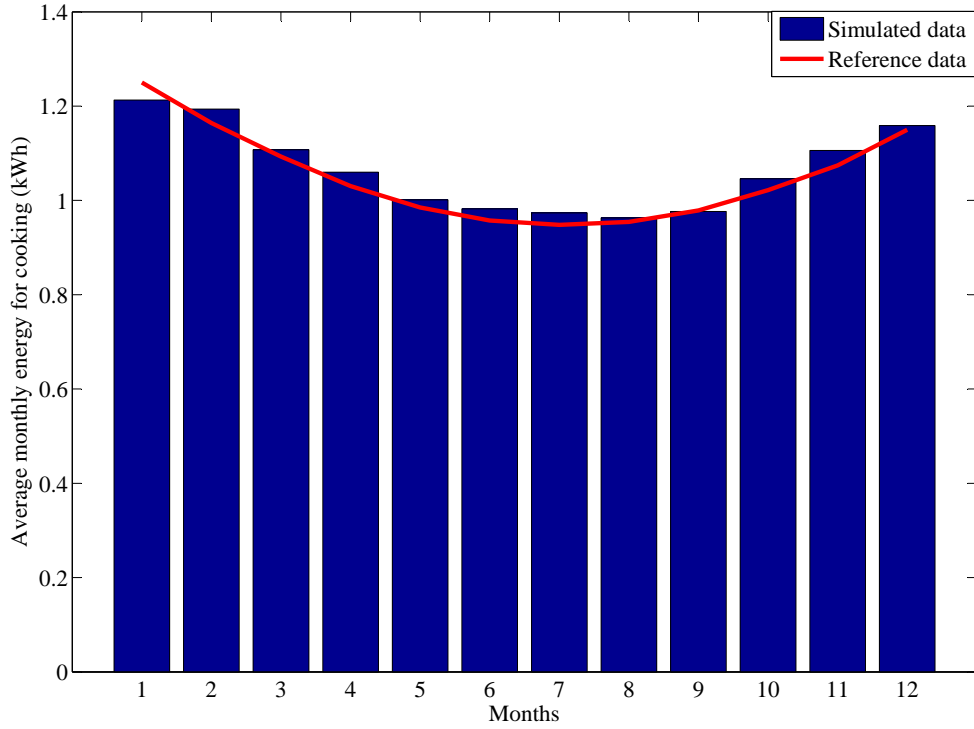
**Figure 3.34:** Power demand during low season comparison between the tool and [123, 124].



**Figure 3.35:** Annual average energy consumption for each load category and in total [1, 101, 123, 124, 125].



simulated by the tool and it is compared with the reference data [101].



**Figure 3.36:** Average energy consumption for cooking for each month compared to [101].

### 3.8 Conclusion

This chapter has described the key stages in the development of a combined Markov Chain-Monte Carlo and bottom-up modelling tool to convert individual residential activity profiles into individual detailed LV electrical load models including both the load profile and the detailed electrical characteristics of LV residential customers. The model is flexible and capable of changing the use or the characteristics of the domestic appliances, allowing for the assessment of DSM in LV networks.

The main advantage of the tool is that its flexibility allows for modelling of various locations by using appropriate TUS data to generate synthesized demand profiles and load models with any specific statistical and qualitative characteristics of customers or appliances. The fact that the model is implemented in discrete stages allows for replacement of certain parts or adding more features on the model.

The validity of the tool was proved by implementing the tool for the UK LV residential sector and comparing the results with publicly available data and statistics. In most cases, it can be seen that there large variations between the available reference datasets in values and time of occurrence of the characteristics of the curves. These variations are obviously inherited to the

results of the power systems studies that use them emphasising the need for more detailed and location dependant datasets.

Regarding the other main advantage of the tool, the development of detailed load models, it can be seen that the presented modelling framework generates detail profiles of ZIP models of the current appliance mixture and it can also calculates the future profiles of ZIP models. These daily profiles can give many more information than just average, nation-wide values like those presented in Table 2.1 allowing for more precise, localised energy management studies. These results are presented and evaluated in the following chapters.

# Future Modification of UK Residential Electrical Loads

---

## 4.1 Introduction

This chapter discusses how the evolution of residential appliances affects the modification of the daily power demand of households underlying the electrical characteristics of the appliances. The methodology presented in the previous chapter is used to develop detailed load models for various scenarios to investigate the effect of the future replacement of older devices by modern technology.

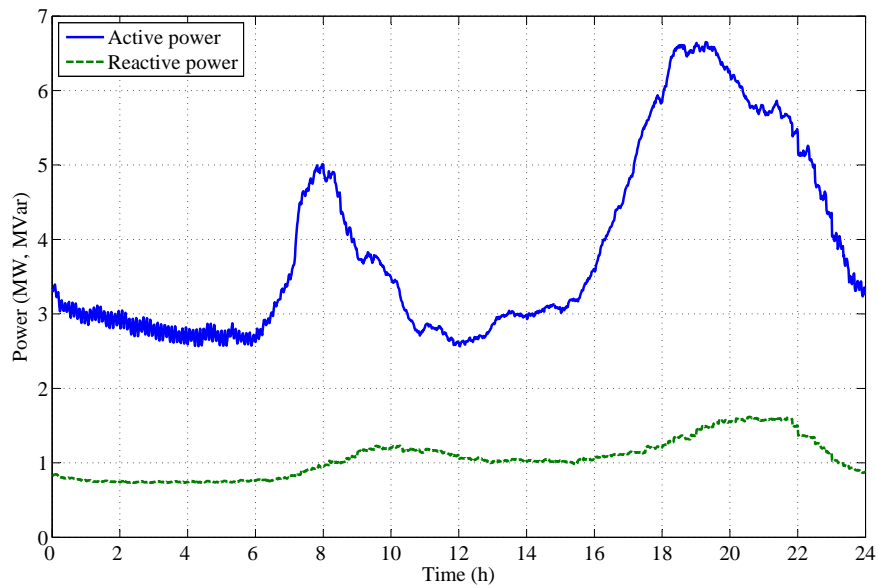
The existing load models for residential customers connected to the LV network are traditionally represented by constant aggregate mean values of their parameters during the day. Previous research has shown the importance of time varying load models for a more accurate simulation of the residential load sector. This is even more clear since the appliances that populate the households and their use are changing and will continue to change in the coming years. This continuous evolution of technology has led to the development of new LV domestic appliances with different load characteristics. Older appliances are replaced by their modern equivalent either because of the regulations, such as general incandescent light (GIL) bulbs by compact fluorescent light bulbs (CFLs) and light emitting diodes (LEDs); or due to new trends, such as cathode ray tube (CRT) televisions (TVs) by liquid-crystal display (LCD) TVs. Although previous studies have focused on the effect of these replacements on the active power demand profile, the difference on the individual load model characteristics has not been studied in any detail.

Various case studies of the most easily predicted technological changes are grouped into scenarios of the future appliance mix and used to study the potential effect of each of them on aggregate load characteristics. Furthermore, a network analysis follows which compares the use of the developed load models in these scenarios and their influence on the operation of the network. In order to accomplish that, a typical model of the LV distribution network of the UK is used to aid understanding of the implications.

## 4.2 UK residential load

For this study, the typical UK residential load sector demand for weekday winter loading conditions has been selected to represent maximum loading conditions. The tool described in the previous chapter was used to develop load profiles for 10,000 individual households. The composition of customers is based on UK-wide demographic characteristics [122]. In Figure 4.1, the temporal characteristics of the aggregate power demand can be seen. There are two peaks, a small one in the morning (07:00-09:00) and a larger one during evening (17:00-22:00) as expected for the typical UK residential load curve, while there are two plateaus at night and mid-day between the peaks.

On the other hand, the reactive power is characterised by two less pronounced peaks that almost coincide in time with the peaks of active power demand. The peaks are shifted to about two hours later and their duration is longer than the active power curve. This indicates that different type of loads are affecting the two curves and a change in one curve is not necessarily translated into a similar change in the other.

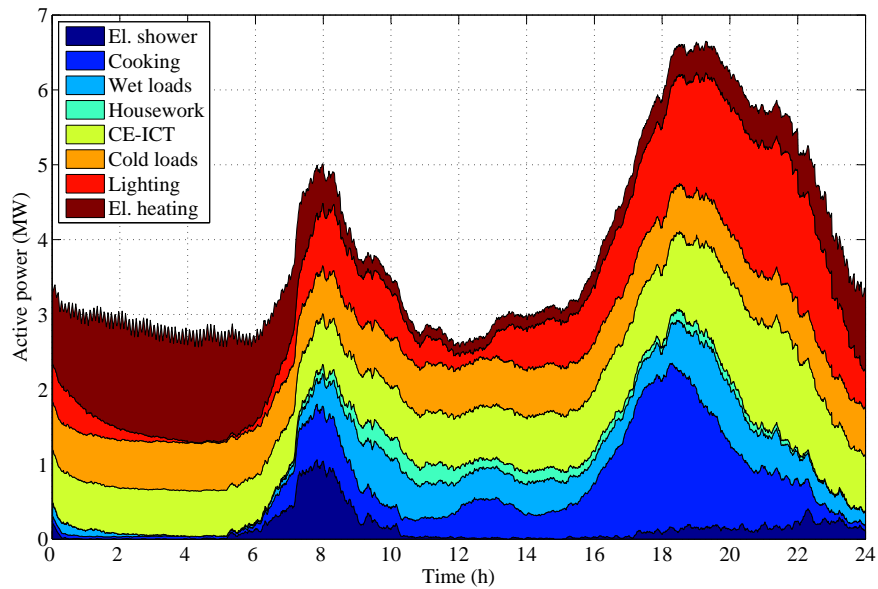


**Figure 4.1:** Typical active and reactive power demand of UK residential sector.

### 4.2.1 Power demand

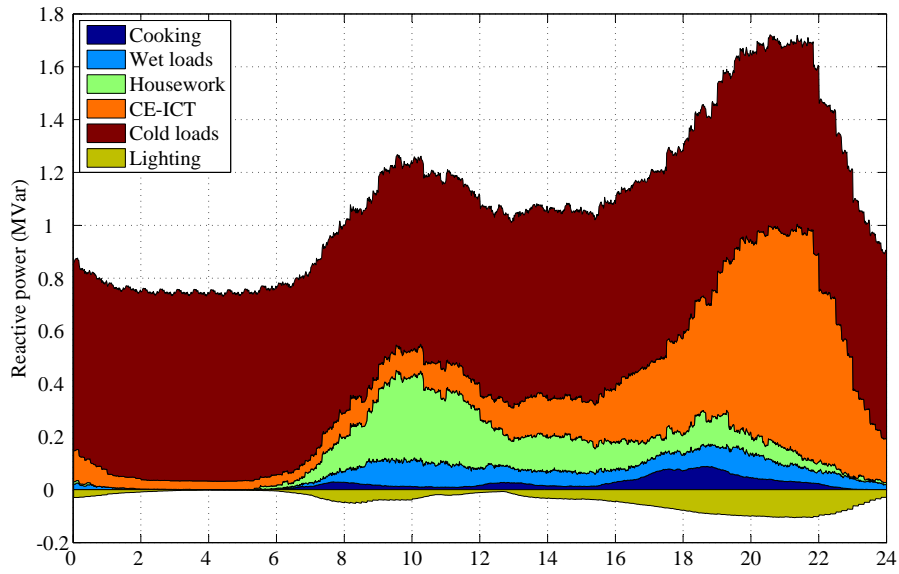
The envelope of the power demand profile does not provide the full picture of the aggregated load. A look at the load composition across the day is necessary to achieve this. The appliances composition of the aggregated load from Figure 4.1 can be seen in Figure 4.2 and 4.3. It can be seen that the load categories that experience the more severe technological changes, such as consumer electronics (CE), information and communications technology (ICT) hold a large proportion of the daily energy consumption in the UK, especially during the evening peak. Also, lighting has a large contribution at the same peak indicating that the change in the light bulbs mixture will affect significantly the future shape of the demand curve.

The composition of the morning peak shows that the contribution of the majority of the load categories is similar, with lighting, electronics and cold loads having the largest share.



**Figure 4.2:** Load mixture of active power demand during winter.

Due to the existence of several resistive loads, such as space heating and electric showers, and the different need for reactive power among the appliances, the composition of reactive power varies from active power. Figure 4.3 illustrates the dominant impact of cold loads on total reactive power and the important amount of reactive power required by CE/ICT. Also, the negative contribution of lighting due to the capacitive behaviour of CFL lamps is noticed.

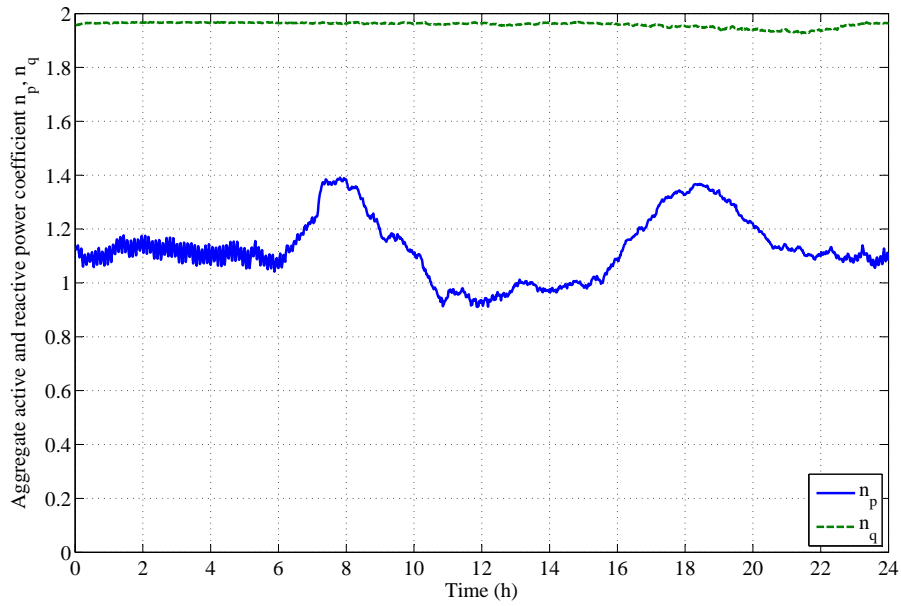


**Figure 4.3:** Load mixture of reactive power demand.

#### 4.2.2 Load model

The aggregate active and reactive power coefficient of exponential load model are presented in Figure 4.4. Because of the physical significance of the load model, there is some correlation between the aggregated active power coefficient  $n_p$  and the active power demand and especially for the peaks. During these periods, more appliances are used and the majority of them are resistive loads, such as cooking appliances, and the value rises towards two. However, the value of the  $n_p$  is close to one and the constant current load type during the most of the day and especially at night where two load categories mostly operate, cold loads and heating. Their contradictory characteristics cancel each other, the motors of cold loads tend to have constant real power characteristics whereas heating loads tend to have constant impedance.

For the majority of the 24-hour period, the coefficient  $n_q$  is dominated by motor loads, and will tend towards constant impedance load type. As the day passes and more loads are used within the household, the value of  $n_q$  will reduce as the contribution from other loads with lower exponent values increases. However, this change is not very radical.



**Figure 4.4:** Aggregate values of active and reactive power coefficient.

### 4.3 Load modification

The technological evolution and the need to create more energy effective devices allow for the development of new appliances to replace the existing ones in future households. Obviously, it is anticipated that the new appliance mixture will affect the aggregate electrical characteristics of the load as well as their response to the network operation.

For this study, the changes that are more likely to happen in the future have been implemented in the household load categories by replacing the corresponding appliances to investigate the impact of the changes. These changes were divided into two time periods; the short-term and the long-term future. The two scenarios that are described here and the results on the load model parameters are presented.

#### 4.3.1 Short-term future load

The changes that are included in this scenario are the following:

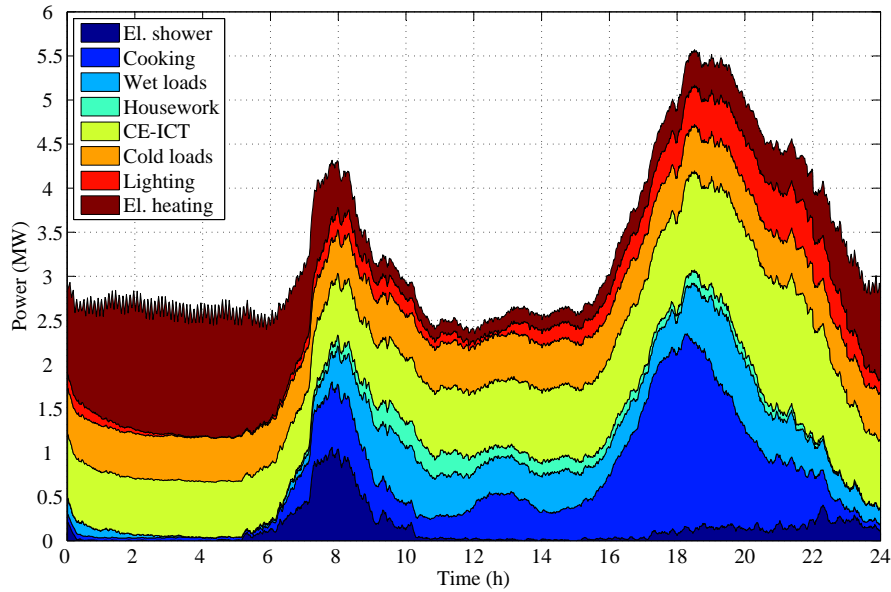
- **Lighting:** Due to the legislation and ban on GIL lamps, the light bulb mixture is expected to change dramatically. Existing GIL lamps are expected to be replaced by equivalent in luminance and more energy efficient CFL's. The percentage of LED lamps is likely to remain almost the same because of their high price.
- **CE/ICT:** Popular trends and the evolution of technology will result in the replacement of old CRT screens of televisions and monitors with LCD and LED technology. Also, the reduction in the upper limit of rated power that the appliances do not require power factor

correction (PFC) circuit from 75W to 50W is included in this scenario. This change was implemented based on the expected change of Harmonic legislation [106].

- Cold Loads: The new appliances that are available now in market are more efficient and according to studies and the manufacturers' datasheets, the duty cycle of the motors is reduced from around 33% to 25%.

#### 4.3.1.1 Power demand

The results from the changes described above are presented here. In Figure 4.9, the maximum active power demand was reduced by 16.7% while the morning peak was reduced by 14%. During the day, the reduction is much less, about 6-10%, and at night-time, apart from the first hours after midnight, the demand remains almost the same. The reasons for the above changes can be explained by Figure 4.5. The changes in lighting reduced significantly the demand at rush hours and the replacement of old energy intensive TV's and monitors affected the required power. As for the cold loads, the decrease in the motor duty cycle accordingly affected the power demand throughout the day.

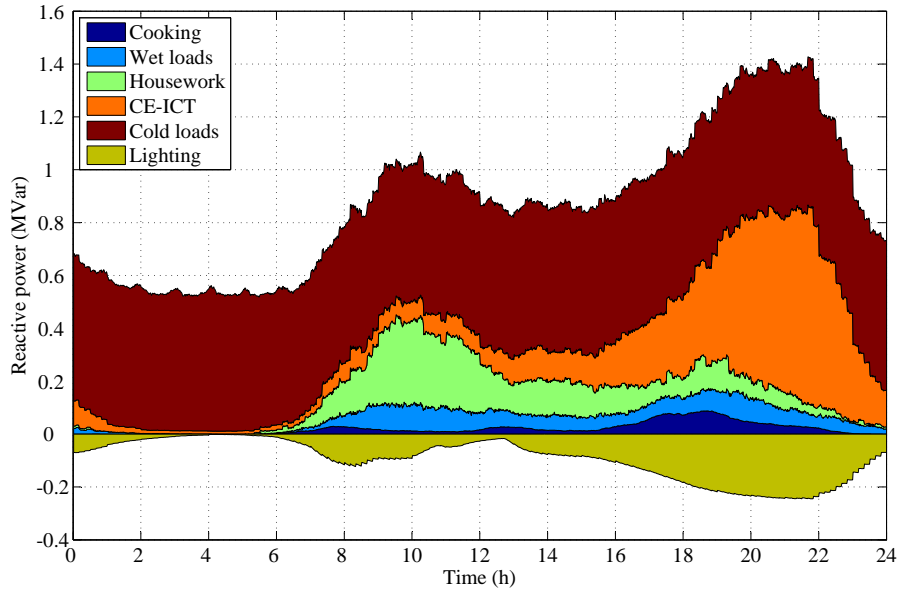


**Figure 4.5:** Load mixture of active power demand in short-term future.

Respectively, a reduction of about 26% in the maximum reactive power compared to the base case is noticed in Figure 4.10. In addition, the reduction of reactive power varies between 16-24% for the rest of the day. According to the Figure 4.6, the reactive power demand of CE/ICT was reduced significantly and affected the evening peak as it represents a large portion of it. The change assumed in the electronics, by replacing the TV's and monitors, would have resulted into a small increase in the reactive power demand but the drop of the limit in rated power that



PFC required has canceled it out. In addition, the massive increase in CFL's has resulted in a large capacitive load that cancels out the reactive power demand further.



**Figure 4.6:** Load mixture of reactive power demand in short-term future.

#### 4.3.1.2 Load model

A significant impact is also noticed on the aggregate active and reactive power coefficient. Figure 4.11 shows that during the evening peak the  $n_p$  reduces due to the reduction of the active power of the electronics and resistive loads, such as GIL. This increases the influence of motors, e.g. cold loads and wet loads, and results in the aggregate value of  $n_p$  tending towards zero. On the other hand, the reduction in the demand of cold loads has led to an increase in  $n_p$  during the night since the effect of resistive load of heating cannot be neutralised as much as in the base case.

With regard to the reactive power coefficient  $n_q$ , Figure 4.12 presents an increase, particularly during evening peak time. This change in the curve can be explained by the application of the new limit of the Harmonic legislation which results in a decrease in the number of appliances without a PFC circuit in conjunction with the presence of a large capacitive load, such as CFL's, and the intense use of these loads during this period.

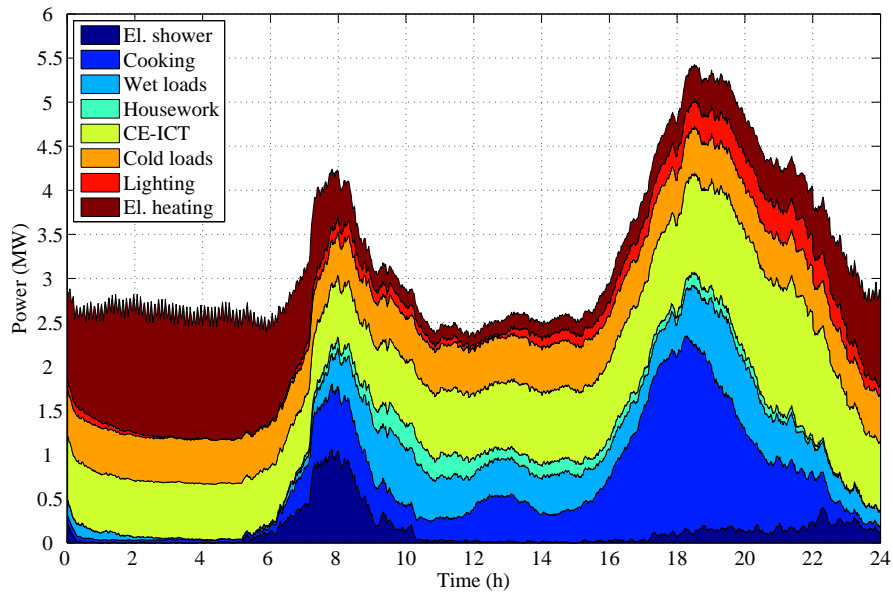
### 4.3.2 Long-term future load

The changes that are included in this scenario are the following:

- Lighting: In the future, it is expected that the vast majority of the light bulbs will be LED's. Thus, in this scenario, all light bulbs are considered to be of this technology.
- CE/ICT: In an effort to make the appliances more energy efficient, it is expected that the appliances without any PFC components will be replaced by appliances with passive PFC circuits and, accordingly, the passive PFC circuits will be upgraded by active PFC circuits.

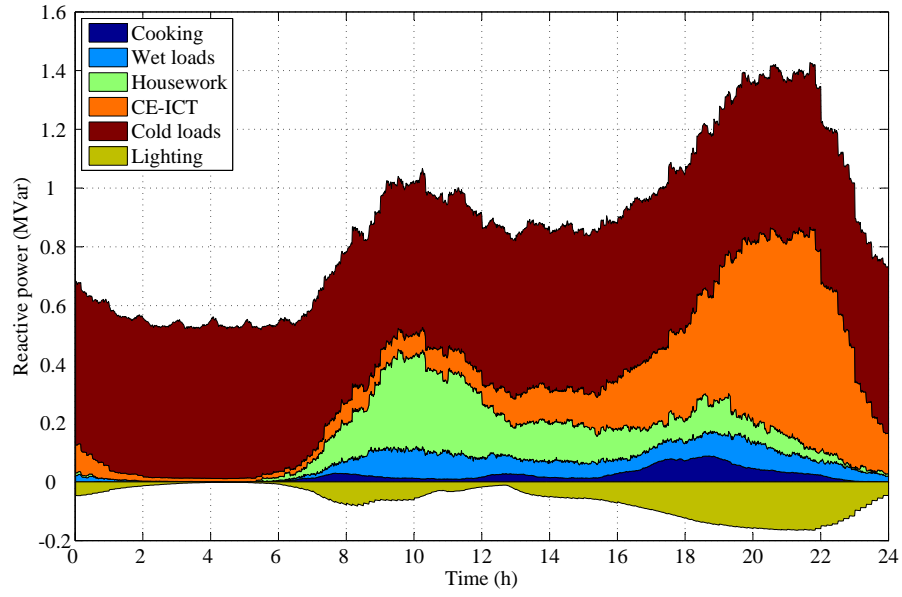
#### 4.3.2.1 Power demand

Active power demand is not expected to be significantly affected by the changes in this scenario. This is verified by Figure 4.7 where a decrease of about 3% is noticed due to the replacement of CFL's with LED's.

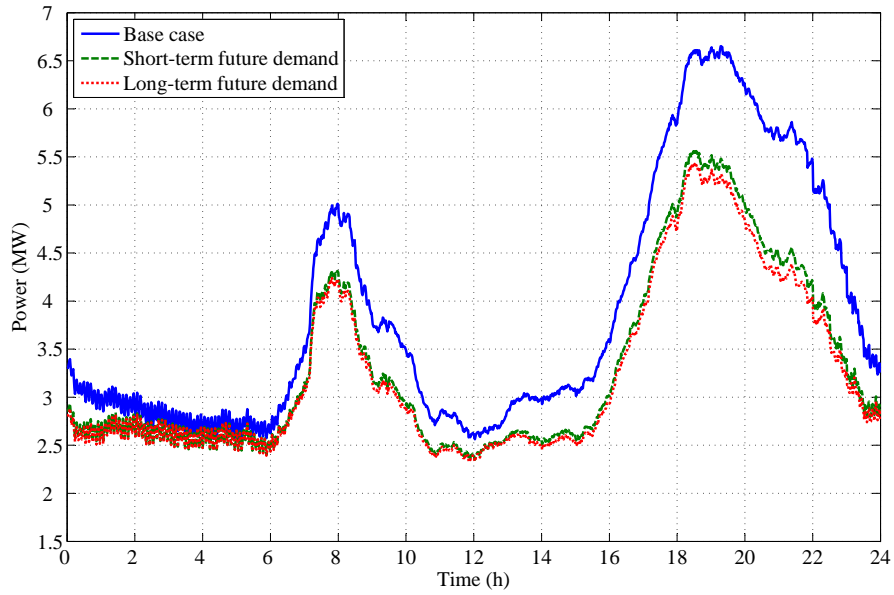


**Figure 4.7:** Load mixture of active power demand in long-term future.

However, the change in the technology of light bulbs and the introduction of PFC circuits, either passive or active, to all electronic devices results in an increase of the reactive power. This is noticeable in Figure 4.8 and 4.10.



**Figure 4.8:** Load mixture of reactive power demand in long-term future.

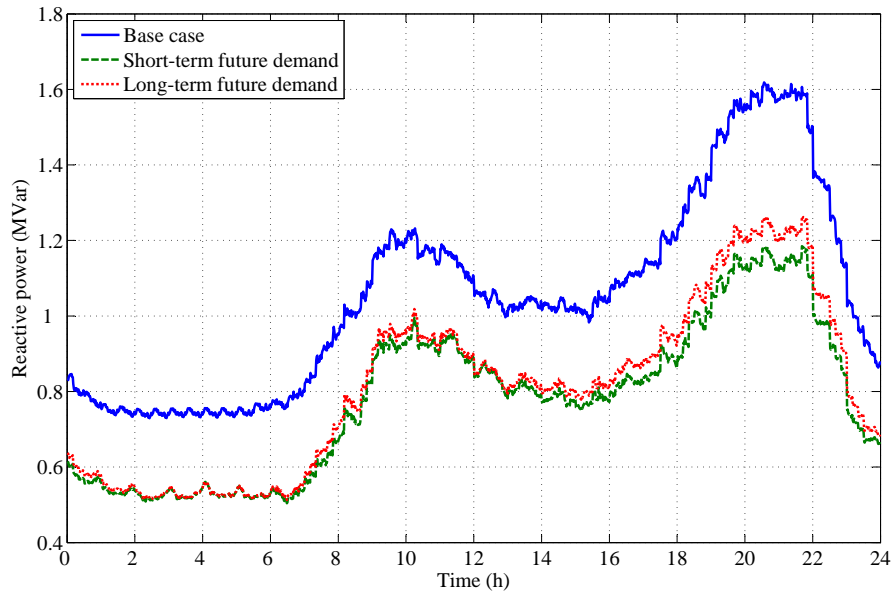


**Figure 4.9:** Active power demand comparison of UK residential sector for all cases.

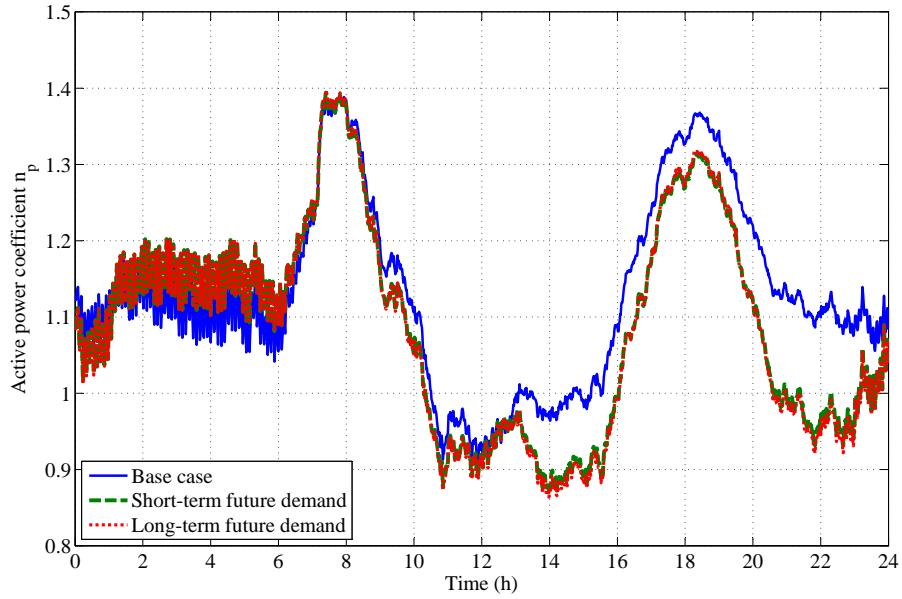
#### 4.3.2.2 Load model

The negligible impact of the changes in load categories on power demand is also visible in Figure 4.11 where the aggregate  $n_p$  is almost the same with the short-term future scenario.

On the other hand, there is a large difference in the aggregate  $n_q$  as seen in Figure 4.12. The fact that the amount of PFC circuits increased, pushed the aggregated  $n_q$  downwards. Furthermore,



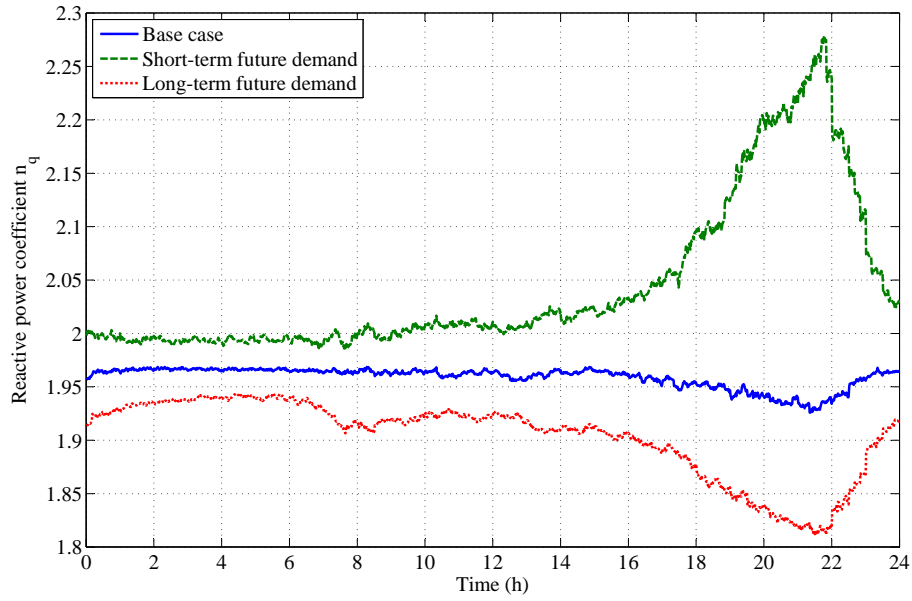
**Figure 4.10:** Reactive power demand comparison of UK residential sector for all case.



**Figure 4.11:** Aggregate values of active power coefficient for all cases.

the absence of the CFL's and their simultaneous replacement with LED's results in the peak during the evening rush hour.

The load models of the developed scenarios that are presented in this section give an overview of the operation of the modelling framework. As it can be seen, apart from the demand profiles, the result of this framework is a much more detailed profile of the polynomial and exponential



**Figure 4.12:** Aggregate values of reactive power coefficient for all cases.

load model coefficients. These results can replace the average daily values of simpler load models in a series of network studies and obtain results that can satisfy the need for a clearer picture of the residential load due to the expansion of the load management implementation.

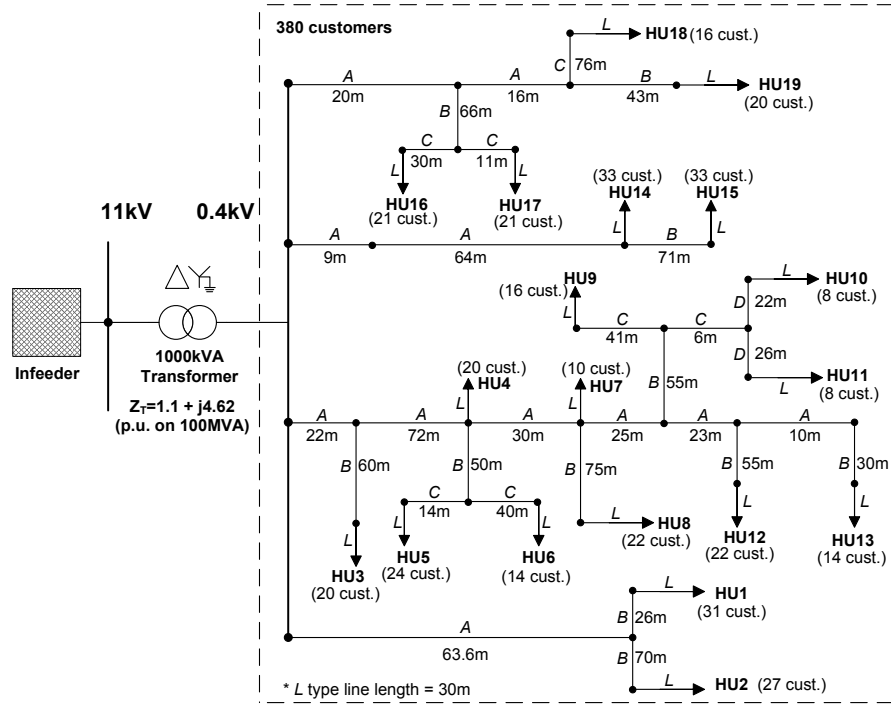
## 4.4 Network analysis

In this section, the scenarios described above are used in a four-wire system for unbalanced network analysis study to assess their impact on network operation.

### 4.4.1 UK LV highly urban network

The model of the typical network of the UK highly-urban (HU) sector is used for the network analysis to produce realistic results is shown below in Figure 4.13. Although the HU sector constitutes a small share of the UK infrastructure, they usually face the more severe energy issues due to the increased demand as they represent households in dense cities and are usually connected on an underground, radial network supplied by an 11/0.4 kV transformer. The network is characterised by high load density and short cable lengths. Four branches are connected to a 1 MVA transformer supplying a total of 380 single-phase customers. The line characteristics of the network can be seen in Table 4.1. More details on the network design and configuration can be found in [126, 127].

This network is populated by 380 customers by design. The profiles that were developed and used for the comparison in the previous sections were divided into 26 groups of 380 households



**Figure 4.13:** Typical network model of highly urban UK residential sector [126, 127].

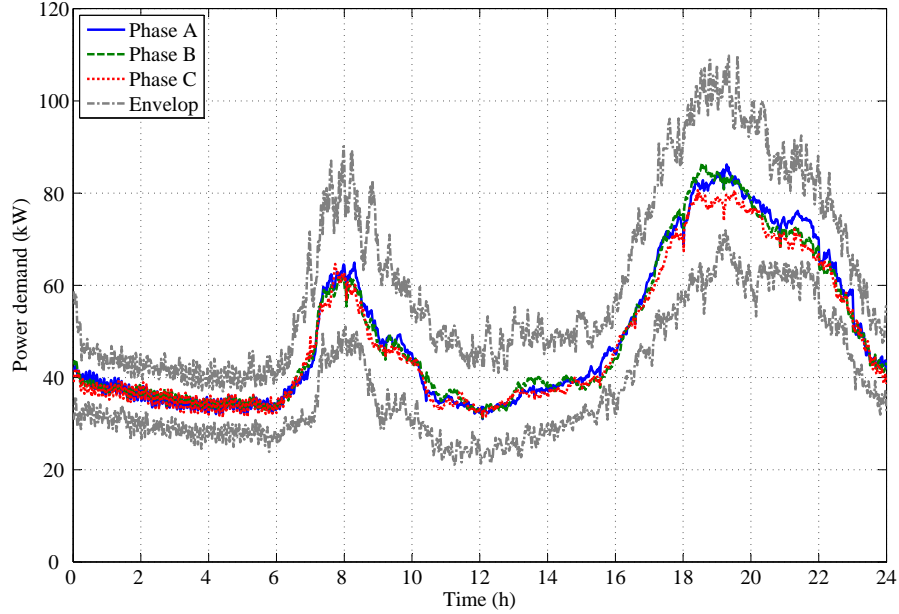
**Table 4.1:** Line characteristics of the typical highly urban network [126, 127].

Line Id.	Cross sectional Area (CSA) ( <i>mm</i> <sup>2</sup> )	Positive sequence	
		<i>R<sub>ph</sub></i>	<i>X<sub>ph</sub></i> ( <i>Ω/km</i> )
Underground Line (Cable)			
A	300	0.1	0.073
B	185	0.164	0.074
C	120	0.253	0.071
D	95	0.320	0.075
E	70	0.443	0.076
Overhead Line			
H	95	0.32	0.085
Service Connection			
L	35	0.851	0.041

maintaining though the demographic characteristics of the UK population. The 26 groups were necessary in order to increase the accuracy of the results due to the small number of households in the network allowing for large variation in the power demand which gets worse considering the separation of the households into the three phases.

### 4.4.2 Results

The active and reactive power demand of the three phases at the first node along with the envelope of the curves are illustrated in Figure 4.16. and 4.17 accordingly. The fact that the load is evenly distributed among the three phases allows the use of only phase A to show and describe the results for presentation reasons.

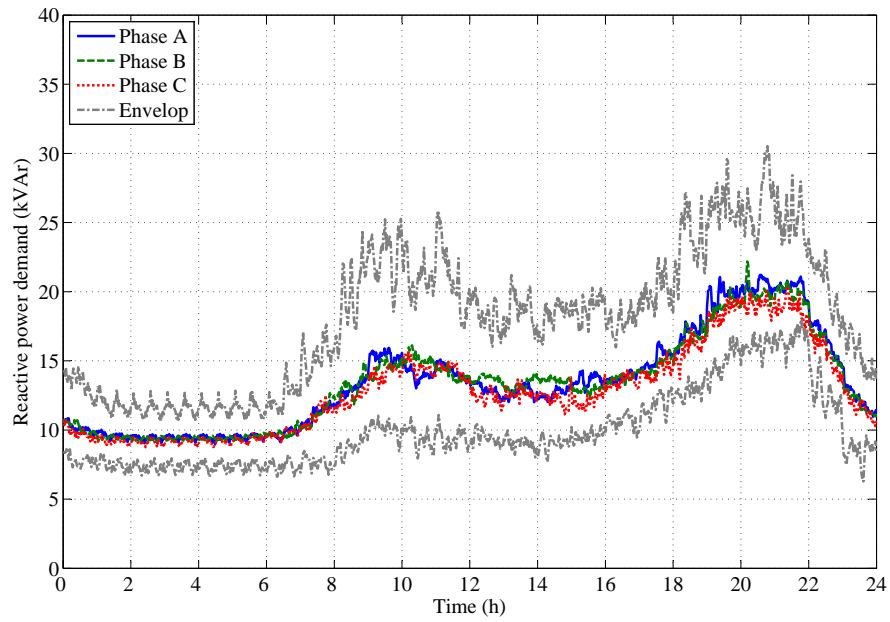


**Figure 4.14:** Average value and the envelope of the active power demand per phase of all simulations

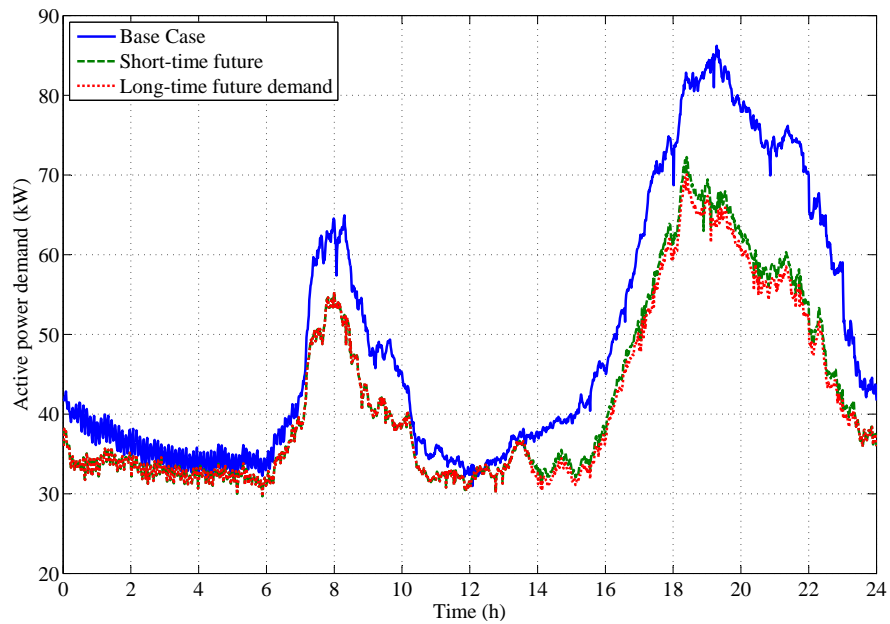
#### 4.4.2.1 Power demand

Figure 4.16 shows the total power demand, including the load and the network (i.e. losses). Although the power demand curves retain the temporal characteristics that are shown in Figure 4.9, differentiate visibly between the scenarios which are affected by the values of  $n_p$ . When the  $n_p$  is lower than one, i.e. mostly during daytime, the difference is less than expected. On the other hand, the difference in the power demand during peak times is enhanced by the increased value of  $n_p$ . Similar conclusions can be drawn from the Figure 4.17.

Regarding the comparison between the scenarios, it shall be highlighted that due to the changes in the load composition, the network losses were reduced by about 25% between the base case and the short-term future scenario and 5% further between the short-term and long-term future.



**Figure 4.15:** Average value and the envelope of the reactive power demand per phase of all simulations

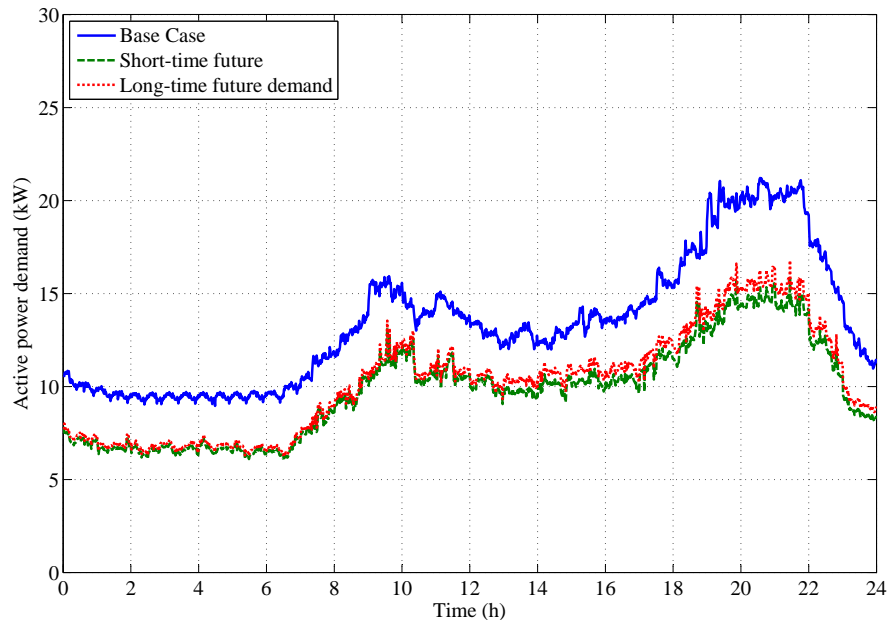


**Figure 4.16:** Comparison of active power demand for all scenarios

#### 4.4.2.2 Voltage

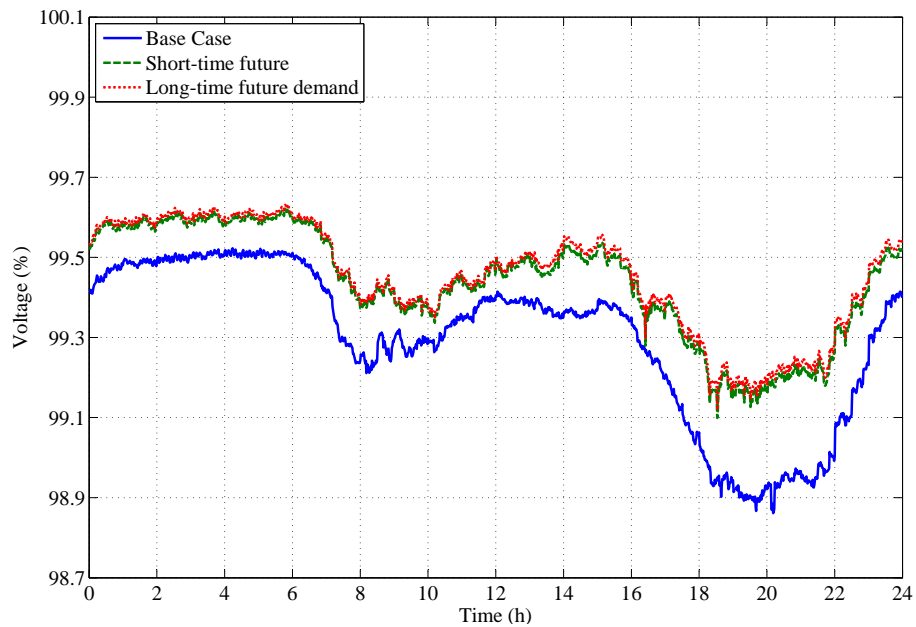
The effect on the voltage on the first node after the transformer is presented in Figure 4.18. The near to 1.5% reduction of the maximum voltage drop can allow for better management of the network. This can be translated into less of a need for implementation of various strategies,



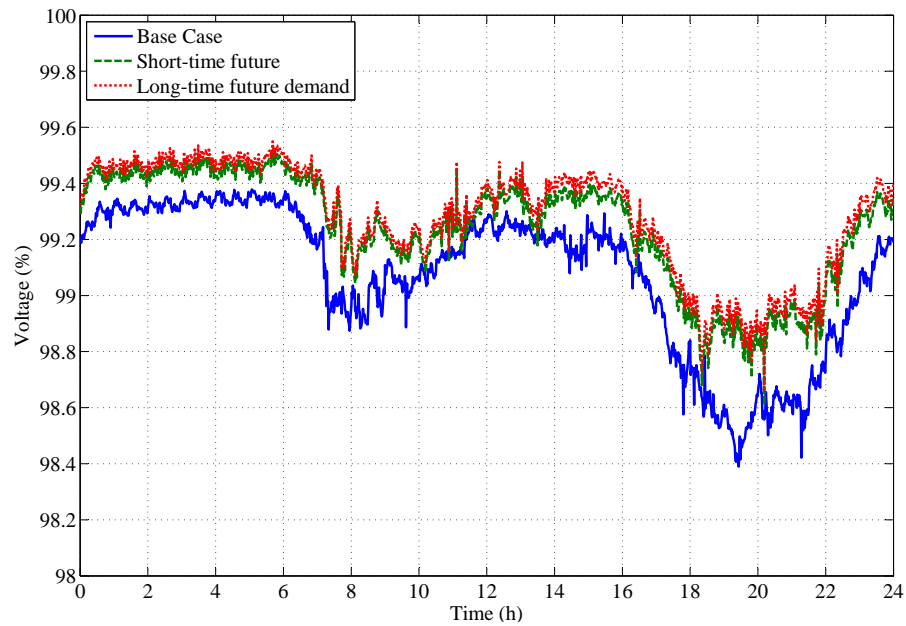


**Figure 4.17:** Comparison of reactive power demand for all scenarios

such as installation of distributed generation, to control the voltage and demand in similar parts of the wider network. With respect to the voltage level of the most distant node, the fact that it increases about 1.5% after the changes shows how much less constrained the network is. Furthermore, this reduction could result in a potential increase of load, i.e. more customers or more appliances, that would not put at risk the operation of the network.



**Figure 4.18:** Voltage level at the first node for all scenarios



**Figure 4.19:** Voltage level at the most distant node for all scenarios

## 4.5 Conclusion

In this chapter, the good operation of the model was presented in a system with no constraints or problems. For this purpose, three developed scenarios were presented to represent the current and the future appliance mix and the load composition. The technological improvements and the need for more energy efficient appliances will result in significant modification to the aggregate residential load. The three scenarios were formatted by dividing this modification into two steps: the base case, the short-term and the long-term future scenario.

The results showed that the total daily energy is expected to decrease while the power demand during the peak hours will also be limited with time. From the power load modelling point of view, there will be a major alteration of the electrical characteristics of the aggregated load which will accordingly affect network operation.

According to the network analysis, the network is expected to become more efficient (since the losses on the network will be reduced as a result of the general reduction of power flows) and flexible (with regard to the available options of managing and/or required upgrading of the network). The following chapters will demonstrate the utilisation of the model for network management to address a range of issues, such as the minimisation of the financial and environmental impact of demand.

# Demand Side Management

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### 5.1 Introduction

In this chapter, an approach for the implementation of DSM on the low voltage (LV) residential load is presented, which includes consideration of device operation cycles. This employs a multi-objective optimisation algorithm in order to achieve the least economic and environmental cost of required daily energy with the minimum effort. The effort is defined as the percentage of the load that is required to be managed [128]. In order to calculate this, the detailed residential load models that are derived from the previous chapter and the long-term future scenario are used to identify the use of ‘non-critical’ loads. The load models are combined with cost and greenhouse gas (GHG) emissions profiles from UK for the winter of 2012/2013 to reform the power demand.

The load management techniques in LV networks varies according to the different load categories and their level of impact on peoples’ lives. LV residential load consists of the various appliances that exist in households and can be divided into two categories according to their necessity: critical and non-critical loads. Although the use of critical loads cannot be modified without changing the behaviour of household occupants, non-critical loads can be deferred so as to achieve the desired targets. An example of non-critical load category is wet loads, such as dishwashers, washing machines, tumble dryers and washing dryers. The operation of these loads can be postponed to another time during the day if needed without noticeable disadvantage to users. Wet loads are responsible for a large percentage of the total daily power consumption (approximately 15%) for the UK [1]. The management of such loads will potentially have an impact on the total power demand, the cost of it to the customers and the total daily GHG emissions. This impact has to become explicit since two of the main selling points of DSM are the reduction in cost and GHG emissions.

At the LV level, the domestic energy demand depends on the mixture of the individual electrical appliances, the behaviour of the residential users and environmental aspects (e.g. external temperature). It is the combination of these three factors which results in the stochastic nature of LV power demand and requires more detailed simulation techniques than those typically applied at the higher voltage levels. This generally requires consideration of the specific loads

available for DSM, as load management must not impact on users' quality of life. The available loads, termed 'non-critical', may be rescheduled without affecting the users. This is demonstrated in several studies that have focused on specific load categories and examine how their manipulation could reduce the cost or the GHG emissions, e.g. electric vehicles (EV) and heat pumps [73, 75]. However, the analysis methods for EVs and heat pumps allow for interruption of their operation. As this is not true for most domestic appliances, the techniques are not directly transferable. For example, load categories such as wet loads, operate in cycles which require that they start and finish without interruption which differentiates them from previous studies on loads such as EVs.

In this study, wet loads are used in the DSM algorithm to illustrate its operation and the use of the modified load profiles in LV network. Furthermore, a sensitivity analysis of the algorithm is presented by using the profiles of the winter of 2008/2009. In this way, apart from highlighting the significance of the price and GHG emissions profiles for the methodology, the difficulty to predict the results of the DSM implementation due to the frequent changes in the energy market.

## 5.2 Methodology

DSM in the LV network focuses, or should do, on the customers' interest which is the reduction of the cost of the daily power demand. Thus, one of the main drivers for the implementation of DSM is the cost that derives from the price of electricity combined with the environmental cost which is defined in this study by generation greenhouse gas emissions (GHG).

The proposed methodology consists of a multi-objective optimisation algorithm for shifting the wet load category during the day. The objectives of the study are to simultaneously minimise the total daily cost of the power demand to the end user and the amount of GHG emissions that derive from supplying the power demand. In order to achieve these targets, the electricity price and GHG emissions profiles are combined in the optimisation algorithm and used as the drivers of the DSM actions on wet loads. A significant parameter is the estimation of the minimum number of shifted loads that are required for the best result.

### 5.2.1 Optimisation problem definition

The objective functions of the proposed algorithm can be described mathematically by the equations (5.1) and (5.2). According to them, the primary targets are the minimisation of the total daily combined cost in the minimum possible number of shifted operations. The combined cost  $c_{comb}$  includes the electricity cost and the equivalent cost from GHG emissions.

$$\min(\sum_{i=1}^t c_{comb} = \sum_{i=1}^t x * c_{wi} + y * em_{wi}) \quad (5.1)$$

$$\min(n_{swl}) \quad (5.2)$$

where  $t$  defines the time steps, which in this study is equal to 1440 minutes,  $c_{comb}$  is the combined cost and is calculated by  $c_{wi}$  and  $em_{wi}$  which are the weighted values of the price and GHG emissions respectively. The weighting factors  $x$  and  $y$  are used to set the ratio of participation of the two criteria in the calculation of the main driver, and  $n_{swl}$  is the number of shifted operations.

The values of the price and GHG emissions,  $c_{wi}$  and  $em_{wi}$ , are in different scale and an immediate comparison is not possible. Therefore, their values are weighted and set between  $[0,1]$  as defined in (5.3) and (5.4).

$$c_{wi} = \frac{(c_i * P_i) - \min(c_i * P_i)}{\max(c_i * P_i) - \min(c_i * P_i)} \quad (5.3)$$

$$em_{wi} = \frac{(c_{em} * em_i * P_i) - \min(c_{em} * em_i * P_i)}{\max(c_{em} * em_i * P_i) - \min(c_{em} * em_i * P_i)} \quad (5.4)$$

where  $c_i$ ,  $em_i$  and  $P_i$  describe the price in £/MWh, the GHG emissions in tonnes of CO<sub>2</sub> eq./MWh and the active power demand in MWh for each time step  $i$  respectively. The constant  $c_{em}$  defines the average cost of the GHG emissions and has been set to £33/tonne of CO<sub>2</sub> equivalent [129].

There are some constraints that need to be taken into consideration. The proposed load management includes only load shifting and, thus, the daily energy should remain the same before ( $E_{old}$ ) and after ( $E_{new}$ ) the manipulation.

$$E_{new} = E_{old} \quad (5.5)$$

Also, in the new load curve, the peak of power demand should be lower than the old load curve. The variation of new demand during the day should be smaller in order to avoid the possibility of concentrating all the shifted load within a short period of time.

$$P_{maxnew} < P_{maxold} \quad (5.6)$$

where  $P_{maxnew}$  and  $P_{maxold}$  are the peak values of the active power profile.

One more limitation is that the load cycle should not be among the two peak time slots, defined in this thesis as the morning peak between 08:00 - 10:00 and the evening peak during 18:00 - 22:00 based on the typical UK residential load curve, after the reconnection. Hence

$$cyc_{wl} \notin [T_{peak}] \quad (5.7)$$

where  $cyc_{wl}$  is the time period of the shifted wet load cycle and  $T_{peak}$  include the periods of peak demand as defined above.

Finally, the fact that wet loads operate in cycles which require that they will start and finish without interruption, is included in the algorithm as a restriction. Also the operation cycles vary in length and magnitude from household to household.

### 5.2.2 Optimisation algorithm

The price and emissions profiles are very important in the load shifting process as they define the disconnection  $t_{disc}$  and reconnection  $t_{rec}$  time step. Their direct correlation, even after the conversion of the GHG emissions profile into the equivalent cost that derives from it, is not possible because of the different scales. In order to be able to control the level of effect of each driver, both profiles are multiplied with the total power demand and then normalised. The profile that occurs is the combined cost  $c_{comb}$ , as can be seen from (5.1).

The  $t_{disc}$  is set by the time of day when the maximum  $c_{comb}$  occurs and the wet load occurrences of this time are selected for shifting. If no wet load is present during the time of maximum  $c_{comb}$ , the nearest operation cycle is selected and used to define the  $t_{disc}$ . The time step of load reconnection  $t_{rec}$  is selected to achieve the targets above without violating the constraints. To fulfill this, the inverse of the  $c_{comb}$  is used to calculate the discrete cumulative probability. The  $t_{rec}$  is selected stochastically based on this probability. The result of that is to distribute the shifted loads more uniformly across the period that is considered as appropriate for reconnection and avoid the creation of a new peak.

## 5.3 Case study

The methodology above is applied to a group of 10,000 households for the scenario that achieved the most beneficial results for the network, the long-term future scenario.

Five cases are considered to study the sensitivity of the effect of the two drivers on the impact on the aggregate power demand. In the first case, only the financial criterion is taken into account, while the GHG emissions driver is ignored. The percentage of the electricity price driver reduces gradually, while the significance of the environmental criterion increases until the financial criterion reaches 0% (Table 5.1). These values were selected in order to cover all possible cases: the optimisation is affected only from one of the two drivers, one driver dominates over the other and the drivers equally affect the optimisation.

**Table 5.1:** The selected test cases on which the optimisation algorithm is applied

Test case	Financial criterion contribution - $x$	Environmental criterion contribution - $y$
Case 1	1	0
Case 2	0.75	0.25
Case 3	0.50	0.50
Case 4	0.25	0.75
Case 5	0	1

### 5.3.1 UK residential load

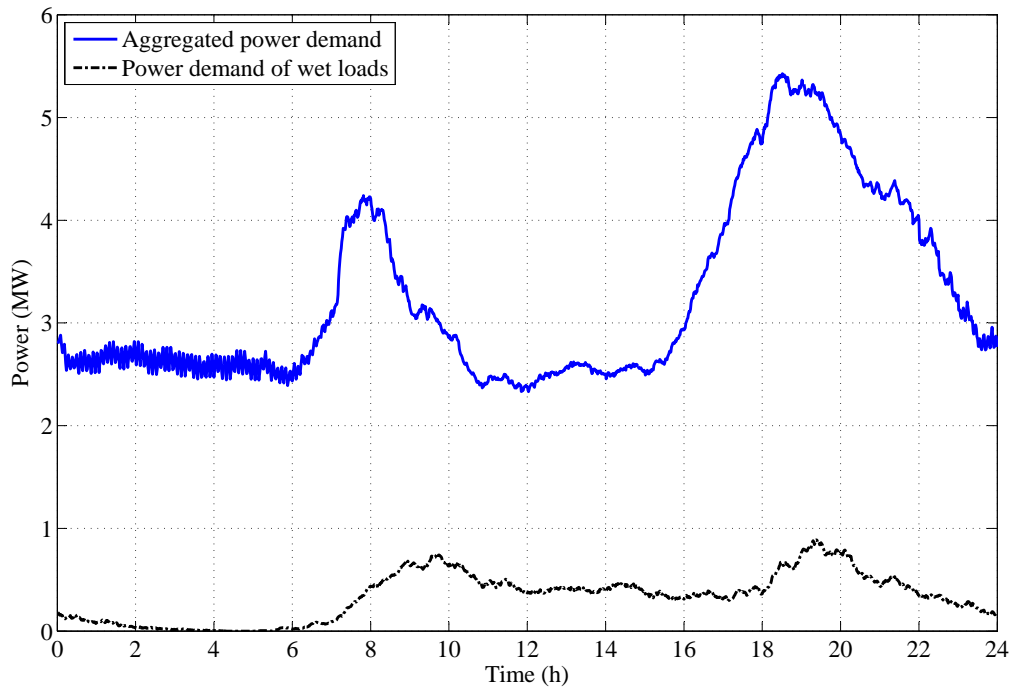
As mentioned earlier, the household profiles of the long-term future scenario were used in this study. The winter weekday has been selected as the time of the simulation, as it is the period that the maximum power demand occurs and also the use of wet loads is most frequent [130]. After all the appliances replacements and the modification of the load mixture occur, the contribution of wet loads in total power demand is even higher, it rises from 8.6% to 10.3%. Thus, an even greater impact is expected due to the application of DSM methods on this load category.

The contribution of the wet load category on the aggregate power demand of the selected group is illustrated in Figure 5.1. It is obvious that the two peaks of the power demand of wet load category coincide approximately with the peaks of the total household demand during winter. This characteristic indicates that a more careful management of this load category could contribute to the main objective of the DSM approach which is decongestion of the power demand during peak periods.

### 5.3.2 Generation price and GHG emissions

Figure 5.2 presents the UK daily profiles of price [73] and GHG emissions for a typical winter weekday, defined by the operating mixture of generation units at each time of day.

Although the cost of electricity for the user is a combination of a number of factors, it mostly derives from the cost of generation. For the purposes of this study, the average electricity price is used. This depends on the contribution of all types of generation plants and remains constant due to long term contracts. Also, the electricity price is mostly formed by power plants that work with fossil fuels, such as oil and coal, because of their high marginal cost. Any load shifting of this magnitude will create changes to the generation of these plants as they respond faster to the demand changes. For these reasons, the average values of price can be used instead of the marginal values. The average value of price for the winter of 2012/2013 (Figure 5.2) is calculated by the daily values of the period between November 2012 and January 2013 from [131]. As can be seen, the price of electricity increases during most of the daytime, while the electricity is cheaper during the night highlighting the need for decongestion of the daytime load.

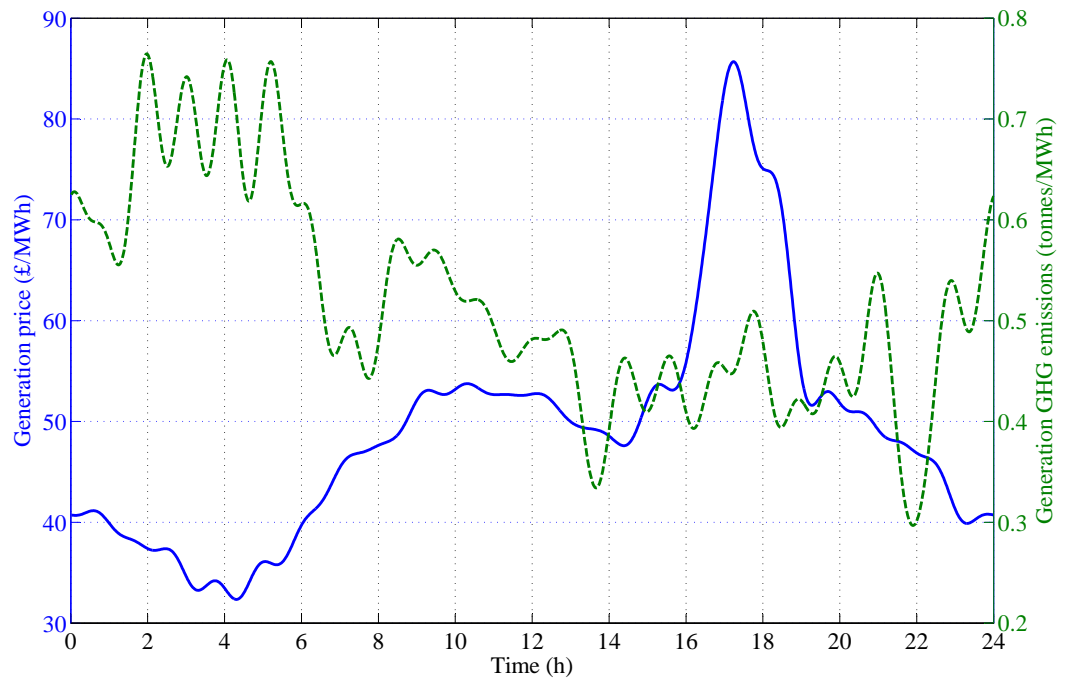


**Figure 5.1:** Power demand of wet loads and the total household demand.

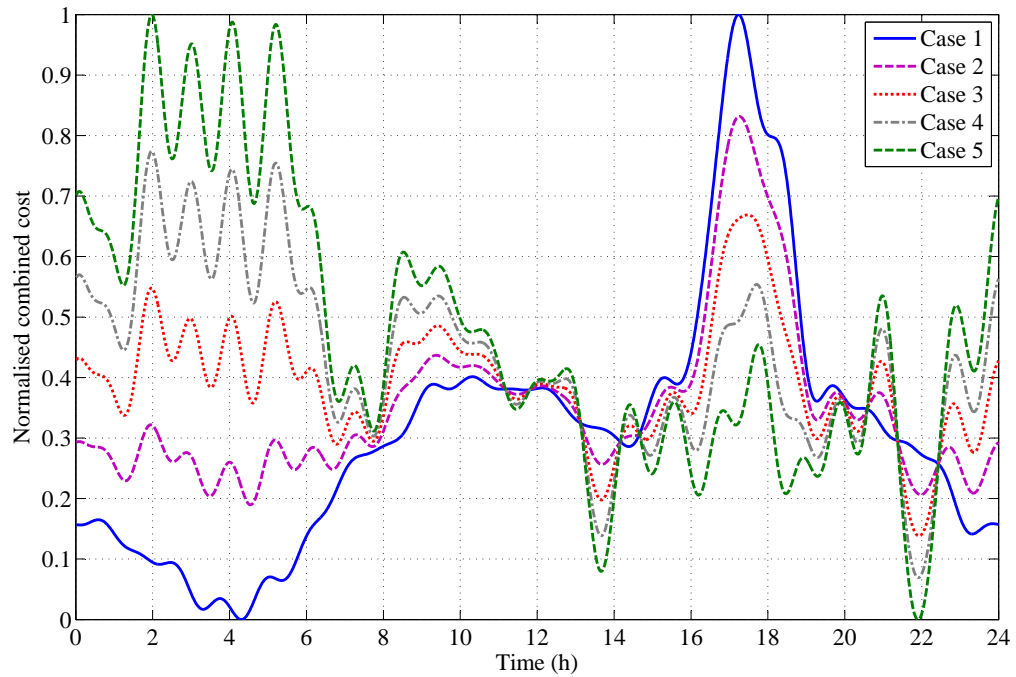
The GHG emissions are the marginal emissions derived from operational data of generation plants on the British grid [131]. Marginal data is required because the shift in non-critical loads will not affect the operation of baseload plants, only those operating on the margin, which tend to have higher GHG emissions intensities. Multiple linear regression was used to determine the marginal emissions factors at different times of day for a typical winter day between November 2012 and January 2013. The method was based upon the one developed by Hawkes [132] and is described in greater detail in [133]. It can be seen in Figure 5.2 that the marginal GHG emissions fluctuate throughout the day, but tend to be higher at times of low demand. This is likely to be due to coal-fired plants being the marginal generators at these times, while gas-fired power stations (which have lower GHG emissions) are the marginal generator at times of high demand. This relationship is mostly determined by the relative prices of coal and gas, suggesting that coal has generally been cheaper than gas.

The contradictory profiles that are shown in Figure 5.2 suggest that a different approach is needed to achieve the required minimisation of each target. Furthermore, they provide a wider variation for the five cases of different combined cost (Figure 5.3). The profiles of the combined costs are calculated in two steps. The two profiles are normalised between 0 and 1 using (5.3) and (5.4) and then they are combined according to (5.1) to create the new profiles.





**Figure 5.2:** Daily profiles of price and GHG emissions per MWh [73, 133] for the winter of 2012/2013.



**Figure 5.3:** Normalised combined cost profile for each case according to Eq. (5.1).

## 5.4 Results of optimisation algorithm

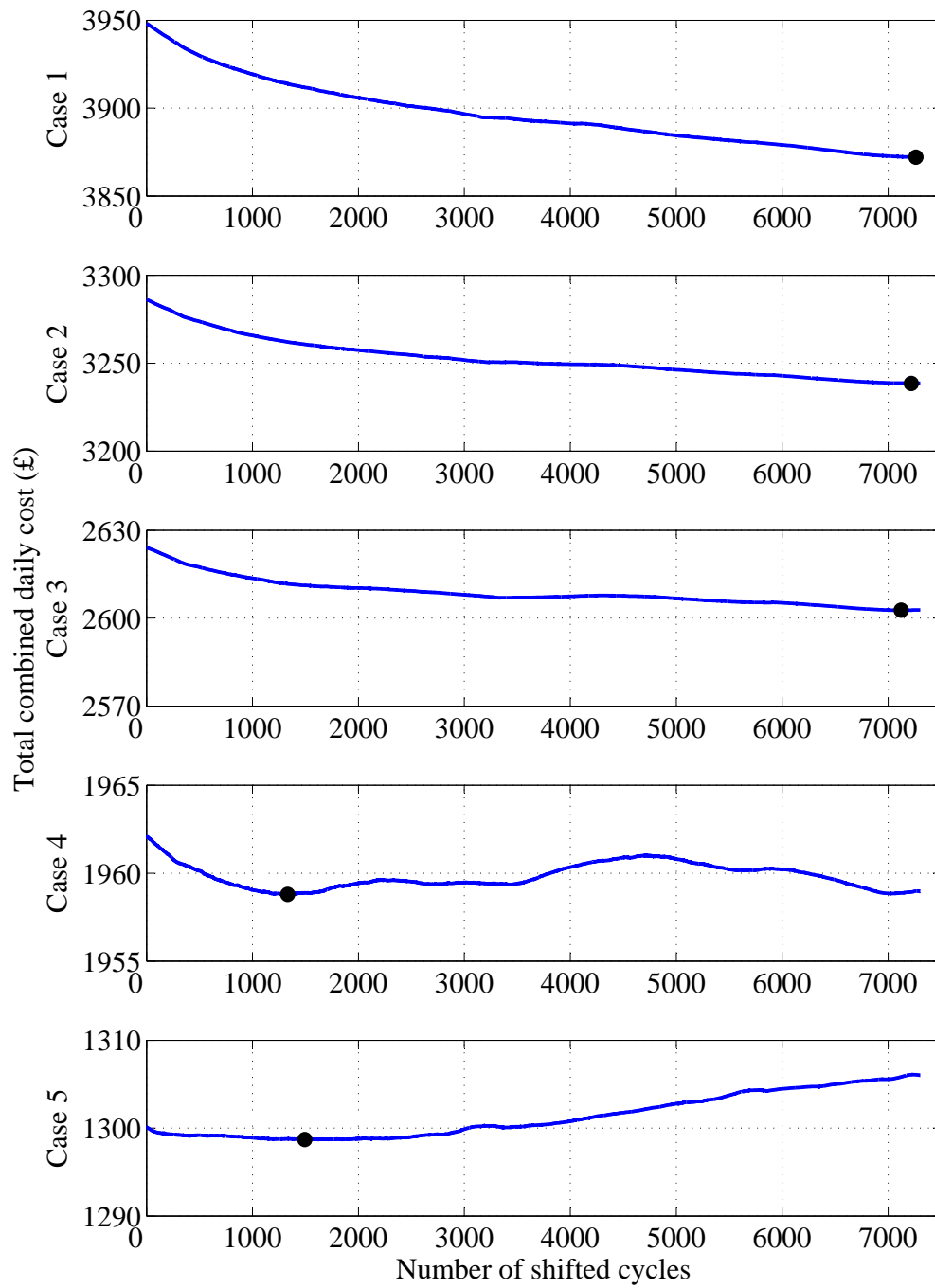
In Figure 5.4, the change in total combined cost for each shifted operation cycle of the wet loads is presented while the black dots indicate the number of required cycle shiftings to achieve the minimum combined cost. It can be seen that as long as the price holds a large share of the formation of the combined cost (Cases 1-3), the savings are greater as more cycles are shifted. In cases 1 and 2, the combined cost reduces at a relatively high rate and continuously until almost all the available cycles of wet appliances have been shifted to a less expensive period. Case 3 is where the contribution of both drivers are equal. The effect of this is shown at the rate of the reduction of combined cost, as it is much lower than cases 1 and 2 and the result of this is to reach the minimum combined cost at less shifted cycles.

In cases 4 and 5, the percentage of the GHG emissions is larger and the shape of the curve changes significantly. The combined cost of case 4 reduces fast and reaches the minimum value at approximately 1350 shiftings. Then, due to the created profile, there is an increase in the combined cost as more shiftings occur. However, it can be seen that the relatively flat profile of combined cost leads again to a reduction at the same level for the first one. The significance of the result in case 5 is that, after the relatively quick occurrence of the minimum value, the combined cost, which actually reflects the GHG emissions, increases by about 1% compared with the initial value.

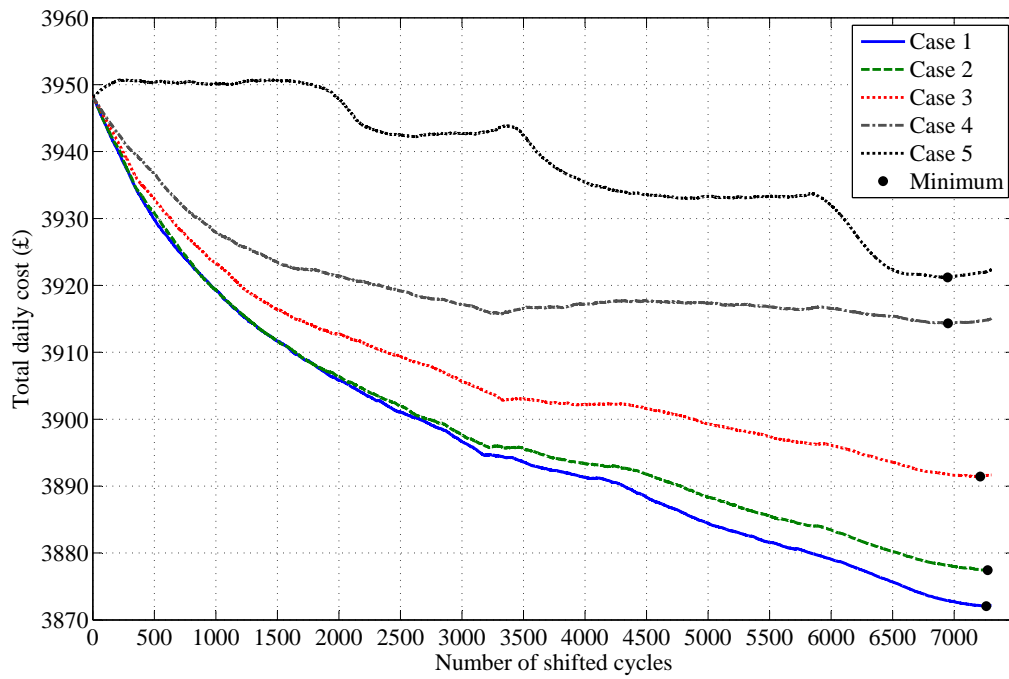
Apart from the combined cost which actually affects the optimisation algorithm, the impact of the shiftings on each of the two drivers independently is also important and is presented in Figure 5.5 and 5.6. It is important to note that in cases 1-3, almost all available cycles shifting are done in order to achieve the minimum value, which is what was also noted for the combined cost. This fact, in combination with simultaneous increase of GHG emissions and their cost, suggests that the cost due to price has greater influence than GHG emissions.

In case 4, the trend is to balance the cost and GHG emissions after about 3500 shifted cycles indicating once more a relatively flat profile of combined cost.

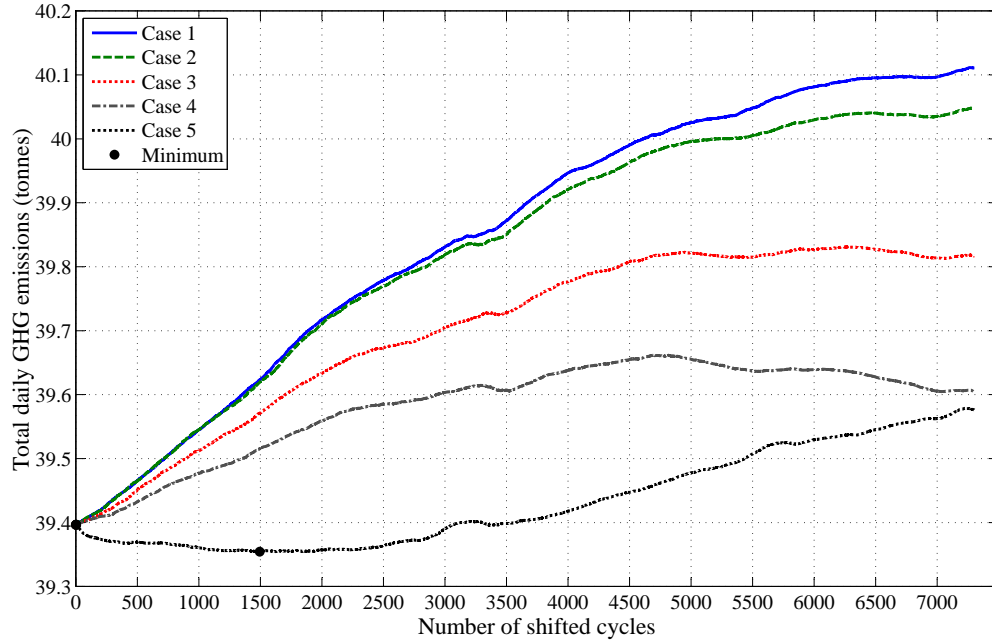
Furthermore, it is noticed that the cost of demand because of the price reduces even when its contribution is zero in the calculation of the combined cost (case 5). However, this reduction does not occur at the same amount of shiftings as in GHG emissions. The reduction in cost comes after the shifting of 2000 cycles, while the minimum GHG emissions are achieved in approximately 1500 shifted cycles.



**Figure 5.4:** Effect of DSM algorithm on total combined cost.



**Figure 5.5:** Differentiation of cost due to price according to the number of load shiftings for each case.



**Figure 5.6:** Differentiation of GHG emissions according to the number of load shiftings for each case.

**Table 5.2:** Savings among test cases

Test Case	Total combined cost savings	Total cost savings	Total GHG emissions savings	Cost of power demand
Case 1	1.9%	1.9%		1.0%
Case 2	1.5%	1.8%		0.9%
Case 3	0.8%	1.4%	<0.01%	0.8%
Case 4	0.2%	0.9%		0.5%
Case 5	0.1%	0.7%	0.1%	0.4%

Although the algorithm is taking into account the combined cost which depends on the given proportions of the two drivers, the real cost is the summation of the two drivers. This cost is illustrated in Figure 5.7. What it can be easily seen is the similarity in the shape of the results with the cost due to price. This is justified by the difference in the volume of the cost due to the price of demand and the GHG emissions.

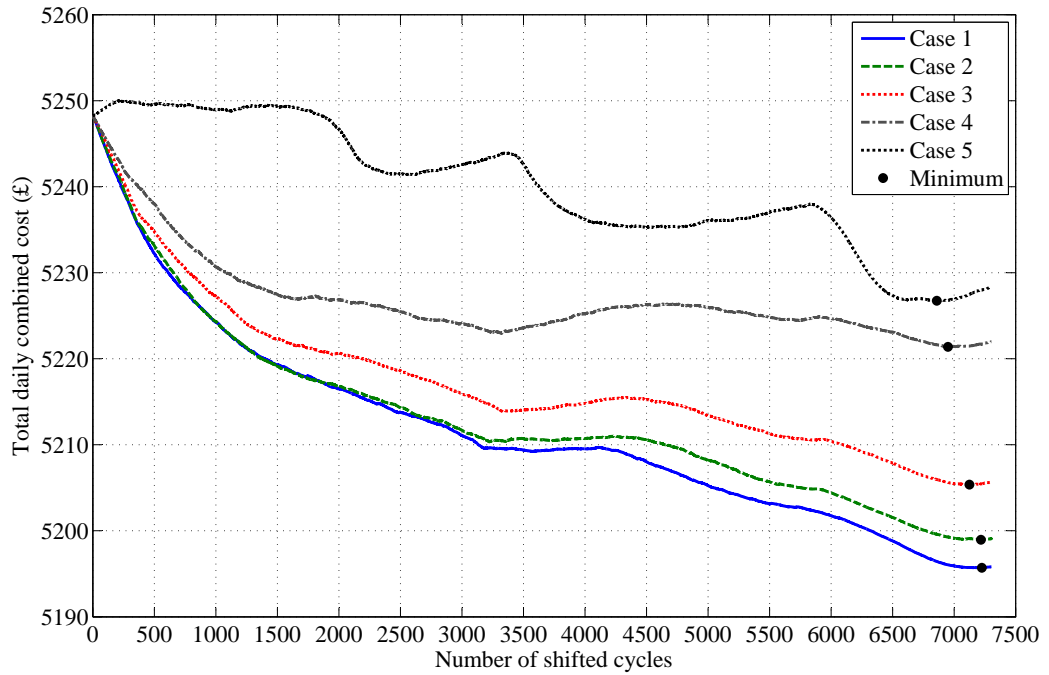
**Figure 5.7:** Variation of the cost of demand after load shiftings for each case.

Figure 5.7 also shows that the maximum reduction on the cost reached about 1%. However, the individual savings on total daily cost and the GHG emissions reached about 1.9% and 0.1%, respectively. This shows the attempt to balance the two drivers, despite the greater influence of price. Further details on the savings for each case are presented in Table 5.2 and the percentage of required shiftings to achieve the savings are shown in Table 5.3. As it can be seen, the relatively small variations in the results demonstrate the sensitivity of the model.

**Table 5.3:** Minimum percentage of shiftings required to achieve the savings among test cases

Test Case	Total combined cost	Total cost	Total GHG emissions	Cost of power demand
Case 1	99.4%	99.4%		98.9%
Case 2	98.8%	99.6%	0%	98.8%
Case 3	97.5%	98.8%		97.5%
Case 4	18.2%	95.2%		95.2%
Case 5	20.5%	95.1%	20.5%	93.9%

#### 5.4.1 Power demand

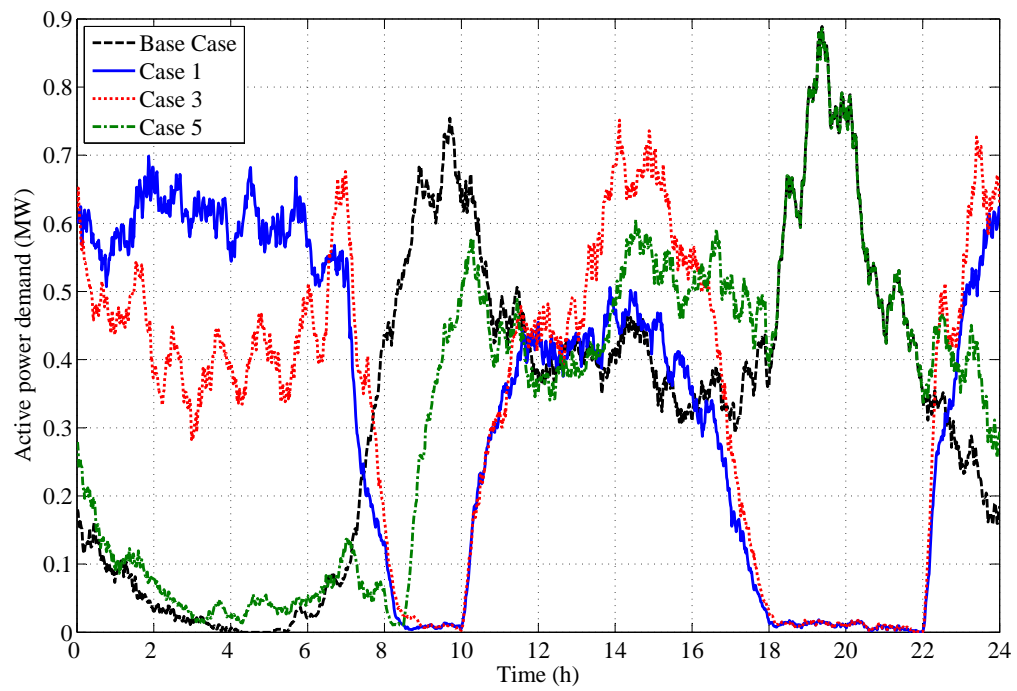
Further details are presented in Figure 5.8, which shows how the power demand of the load category of the wet appliances reshapes after the management technique is applied in all cases.

Intuitively, in the cases where the weighting favours cost over GHG emissions, it is observed that the operation of the wet loads is limited during the daytime when the electricity is more expensive and the majority of the wet load has been shifted towards the night-time. However, the increased consumption during early in the morning is the reason behind the increase of the amount of emissions in these cases (Figure 5.6). In case 5, the increased influence of GHG emissions on the combined cost is perceptible on the new power demand curves. Also, it is clear that the increased demand after midnight (00:00-04:00) reduces the electricity price enough to cover the cost of the demand during daytime when electricity is more expensive, this explains the fact that the total cost reduces in case 5 (Figure 5.7). The result of avoiding the reconnection of loads during peak hours is also visible.

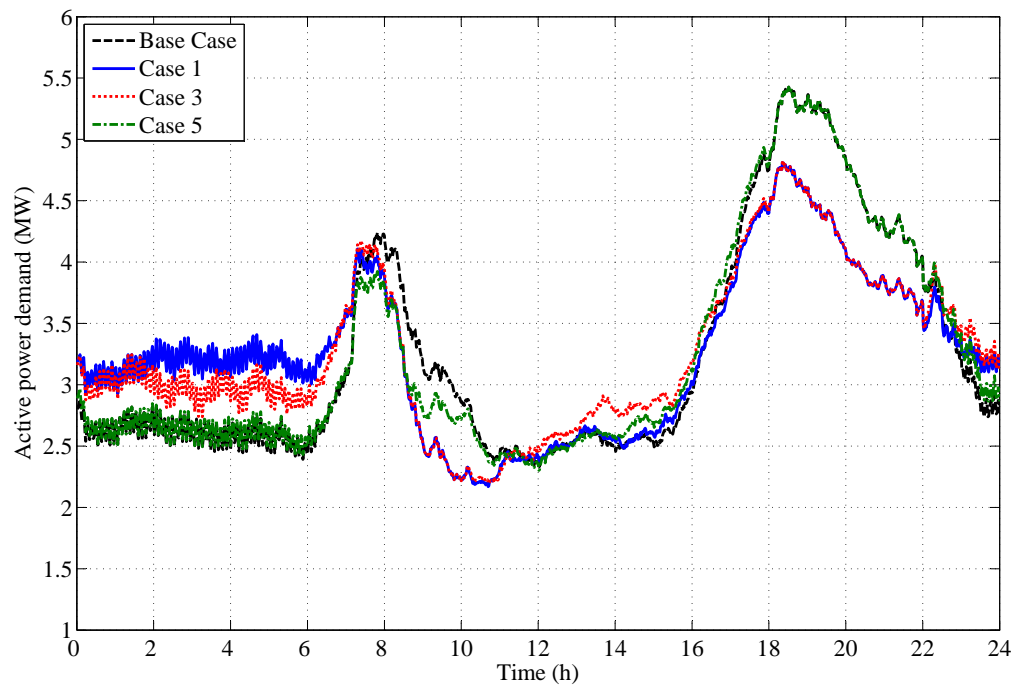
The effect of the reformed power curve of the wet loads on the aggregated power curve is demonstrated in Figure 5.9. The power during the peak hours has been reduced by around 11.9% in the evening and 22.7% in the morning which will clearly help to alleviate stress in the electrical network. Also, the duration of the morning peak has been reduced. The power during night time has increased significantly from 16.7 to 23.5%, according to the case and time. The power demand decreases or remains constant during midday for case 1 and increases for cases 3 and 5, showing the influence of the weighting between the financial and environmental criteria. The power demand during this period increases by up to 12.4%.

#### 5.4.2 Energy saving margin from managing wet loads

Despite the optimisation of the power demand of wet loads based on the drivers that have been described here, it is interesting to calculate the maximum energy of the wet appliances occurrences that could be managed in the ideal scenario of an overall implementation of DSM. As it was shown, DSM actions may take place at any time during the according to the system needs. Thus, it is important for the utilities to know how much energy is available for management in the upcoming time period. The bottom-up modelling approach that has been used, allows for



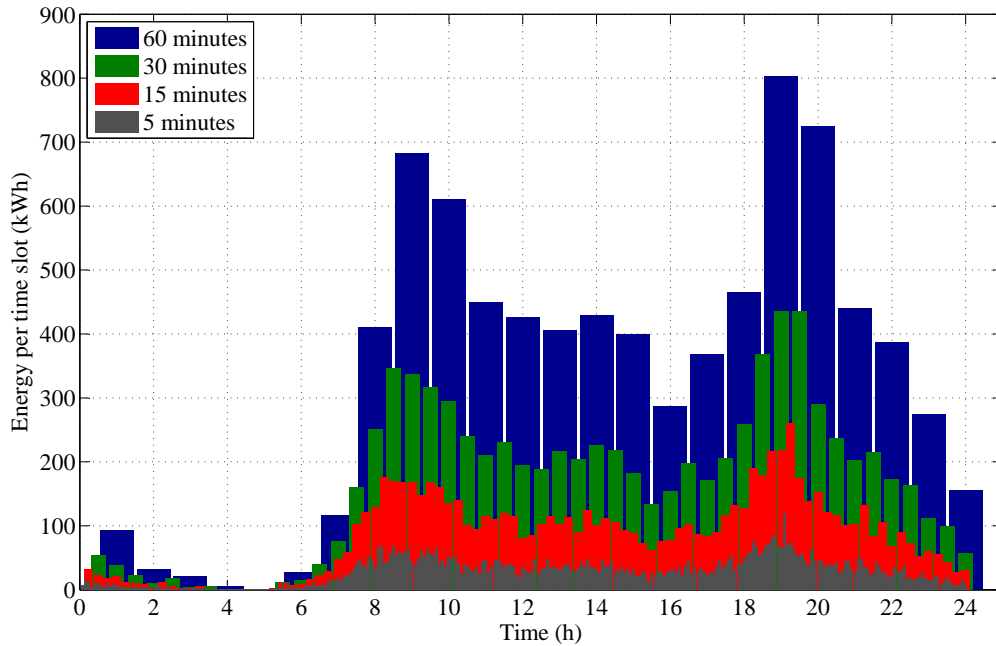
**Figure 5.8:** Active power demand of wet loads before and after load shifting for minimum daily cost.



**Figure 5.9:** Total residential demand profile before and after load shifting for minimum daily cost.

calculating the power demand and the energy required for every household appliance for the duration of these periods. Therefore it can become a valuable forecasting tool that will allow the energy supplier to estimate the effect of a DSM action ahead of its implementation.

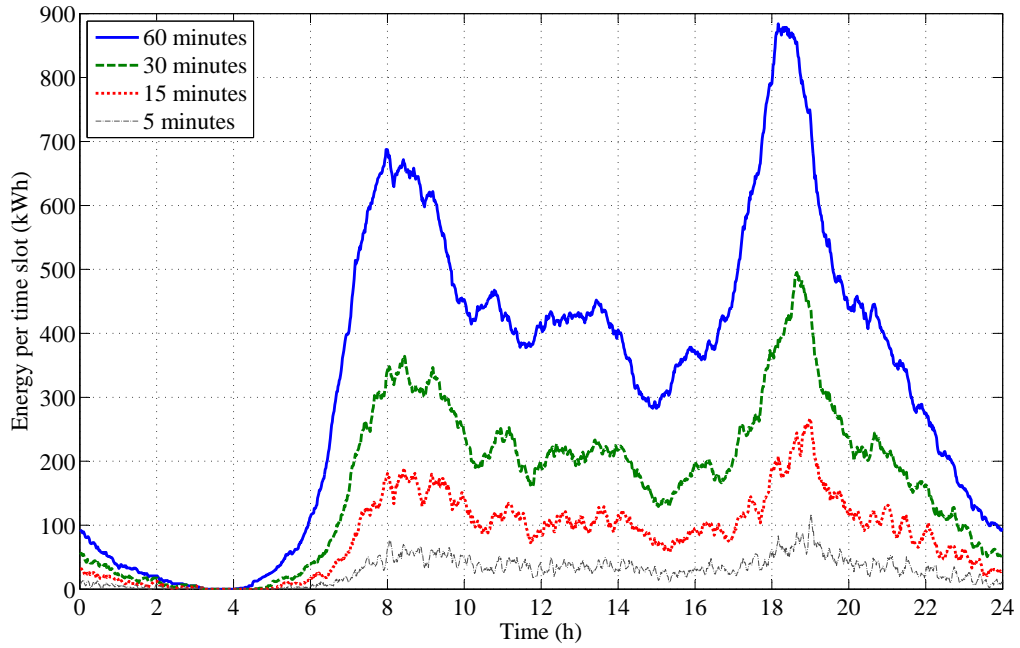
In order to extract this information, the look-ahead time slots have been set as: 5, 15, 30 and 60 minutes in two modes: fixed and rolling time slots. Within these slots, the total amount of energy available for DSM is calculated, as the aggregated energy that will be required during this time slot, by appliances that are expected to start within this time slot, but have not started before the start of the time slot. Although appliance usage could carry on for longer than the time slots, the energy saving margin is calculated by the total demanded energy of the occurrences of wet loads during each time slot. Figure 5.10 presents the energy saving margin for the four cases of fixed time slots. The concentration of the energy from wet loads at the peak times does not surprise but it is interesting that, by reducing the time slot duration it can be noticed an almost uniform distribution of the energy in the morning peak, while the evening peak retains the characteristic peak at approximately 6pm.



**Figure 5.10:** The total energy of wet load occurrences in fixed time slots with four different durations, 5, 15, 30 and 60 minutes.

Figure 5.11 shows the energy saving margin for the same four cases of time slot duration but this time they are rolling for one minute each time. This different approach reveals the potential energy saving at any time of the day, showing that depending on the applying time of the DSM actions, a higher amount of energy could be saved. This is more obvious during the night peak where the energy saving margins can reach almost 900kWh compared to 800kWh (Figure 5.10).





**Figure 5.11:** The total energy of wet load occurrences in time slots with four different durations, which roll every one minute.

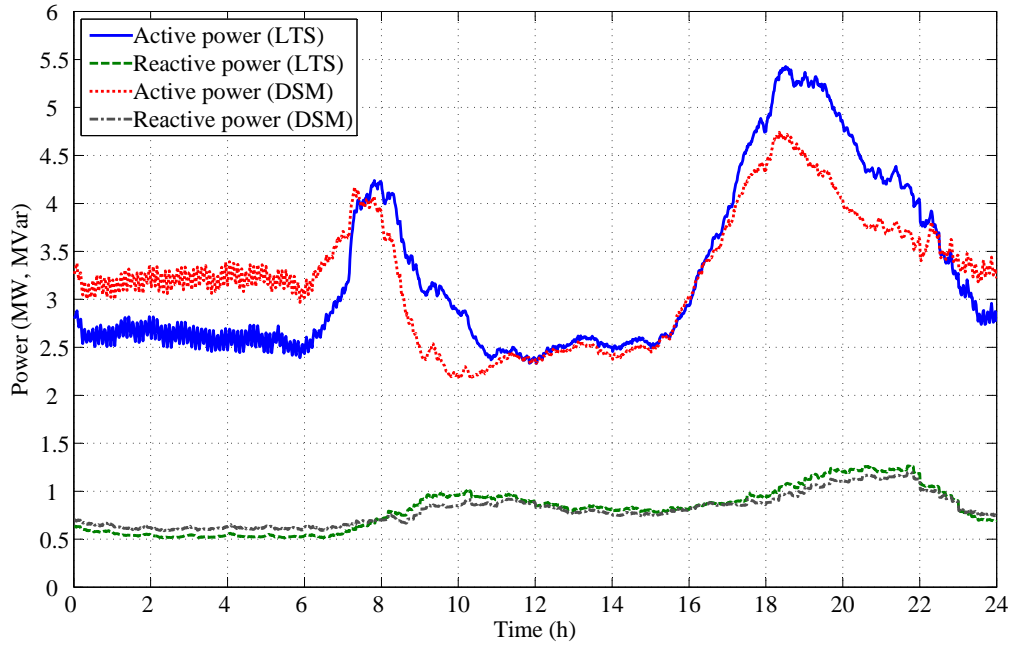
## 5.5 Network analysis

In order to complete the study, the effect of the new load mixture occurring after the DSM implementation on the highly urban network was also investigated. The case with the higher savings, case 1, was selected for the network analysis.

### 5.5.1 New load mixture

The implementation of DSM actions on the power demand on a representative group of UK population results in a different distribution of demand during the day by maintaining the total daily energy demand (Figure 5.12). The change in active power demand has already been discussed, but there is an interesting effect on the reactive power as well. The changes on reactive power follows the equivalent changes in the shape of the active power curve. However, the reduction of up to 9% in the evening peak and 12.5% in the morning peak, in conjunction with the up to 13% increase during night, resulted in a smoother curve after the load shifting due to smaller variation of the values.

Furthermore, load shifting has altered the mixture of the appliances that constitute the power demand at each time step. As a result, the electrical characteristics of the aggregate load have changed as well. The new aggregate active power coefficient is following the active power demand and has undergone significant change compared to the equivalent of the long-term

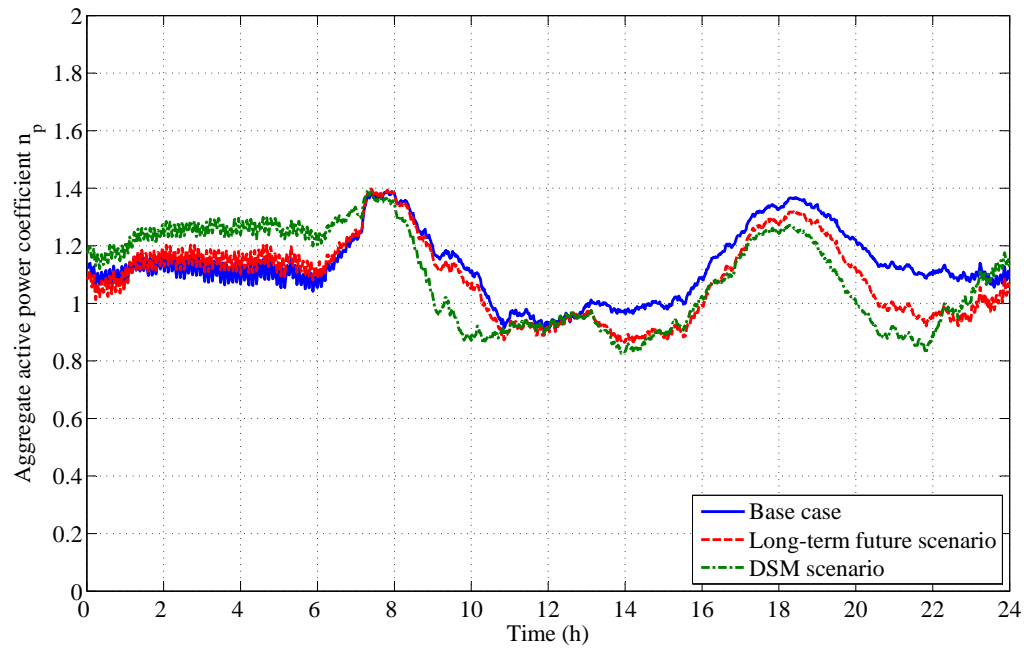


**Figure 5.12:** Comparison of active and reactive power demand between long-term scenario (LTS) and after implementation of DSM.

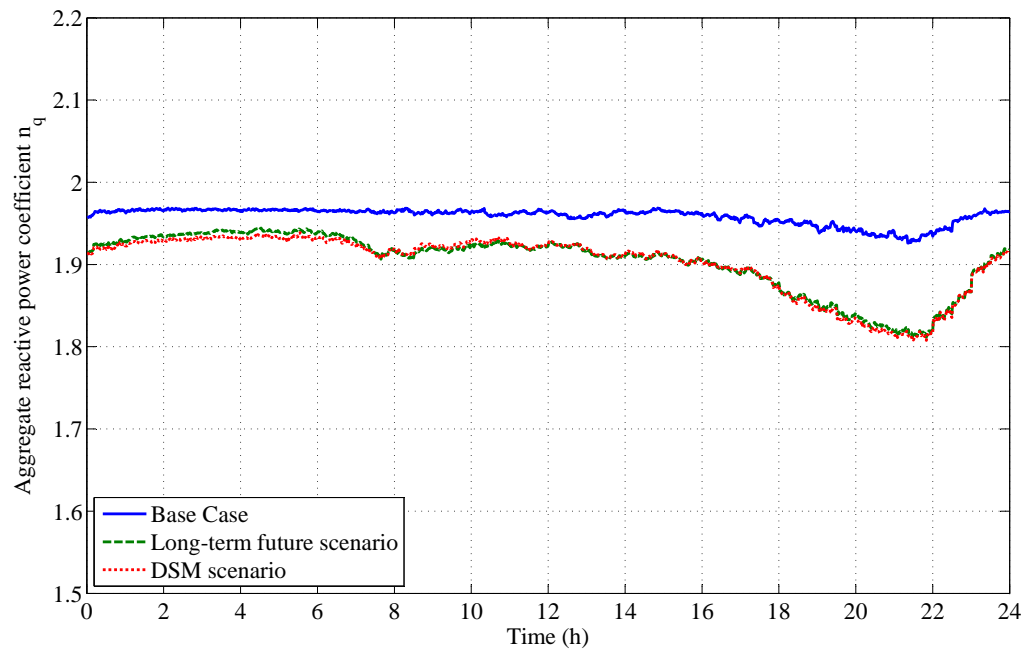
future scenario and the load model of the base case.  $n_p$  has increased during night-time due to the increased presence of resistive loads which holds a large share of the wet loads while they heat up the water (or air in case of tumble dryers). For exactly the opposite reasons, it can be noticed that  $n_p$  is reducing during the day.

In addition, the percentage of motors in the total energy of wet loads is relatively small because of their lower demand against resistive heating elements. Thus, the impact of motors on  $n_p$  due to load shifting is much lower. The increase of  $n_p$  is noticeable only during night-time because the motor load from the cold appliances, is enhanced in comparison to the wet load.

In order to run the network analysis, the typical highly urban network was used and the above set of households were grouped into 26 simulations of 380 customers each as defined in Chapter 4. In all these groups, the percentage of DSM implementation has been kept at the same level of case 1 (Table 5.3).



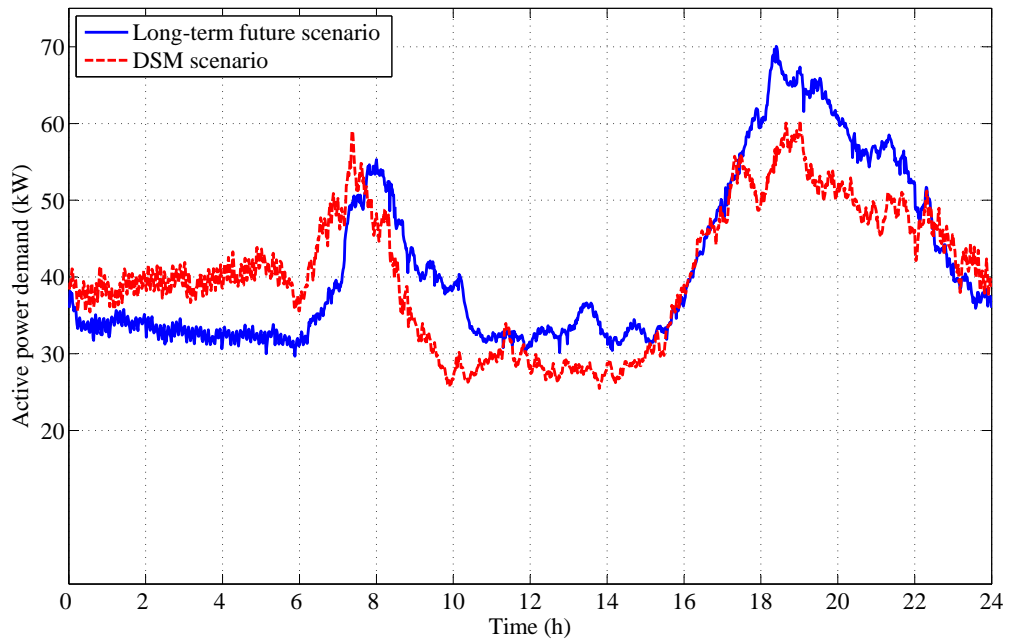
**Figure 5.13:** Comparison of aggregated active power coefficient between the cases.



**Figure 5.14:** Comparison of aggregated reactive power coefficient between the cases.

### 5.5.2 Results

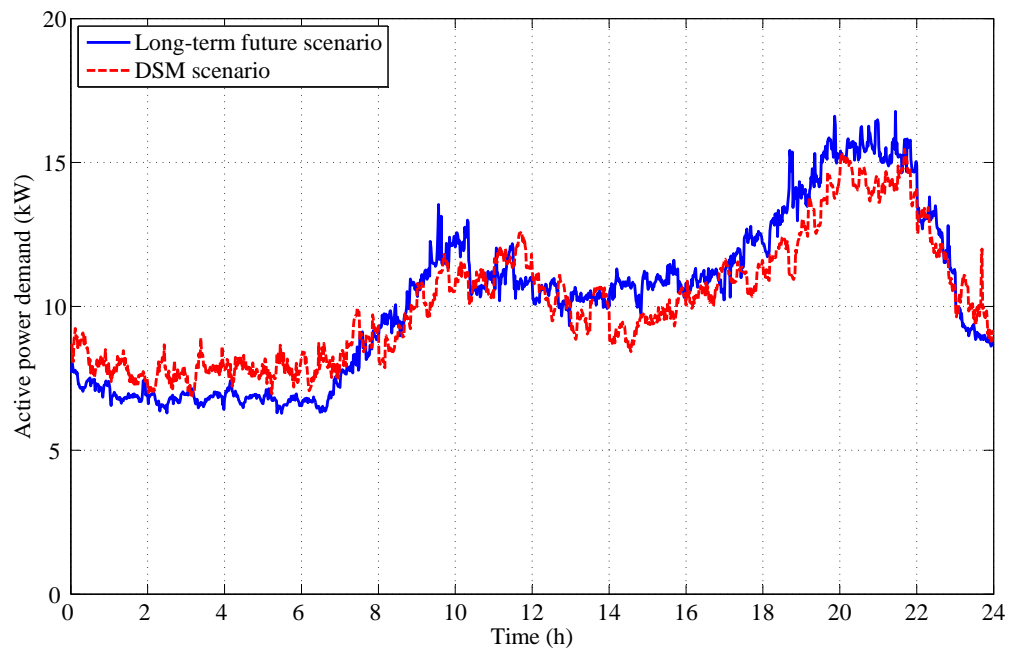
As in Chapter 4, the results of phase A are presented here as the three phases are balanced and DSM was implemented equally in all of the customers. Figure 5.15 shows the power demand of the load at the first node of the network, including the effect of the network, while Figure 5.16 shows the results on reactive power. It can be seen that DSM implementation has managed to clip the evening peak and resulted in a more smooth curve of active and reactive power demand. As for the morning peak, it has been shifted around half an hour towards earlier in the morning in active power demand but about an hour later for reactive power. This is because of the change in the balance between the other loads, mainly electronic appliances, and the motors after the shifting of the wet loads.



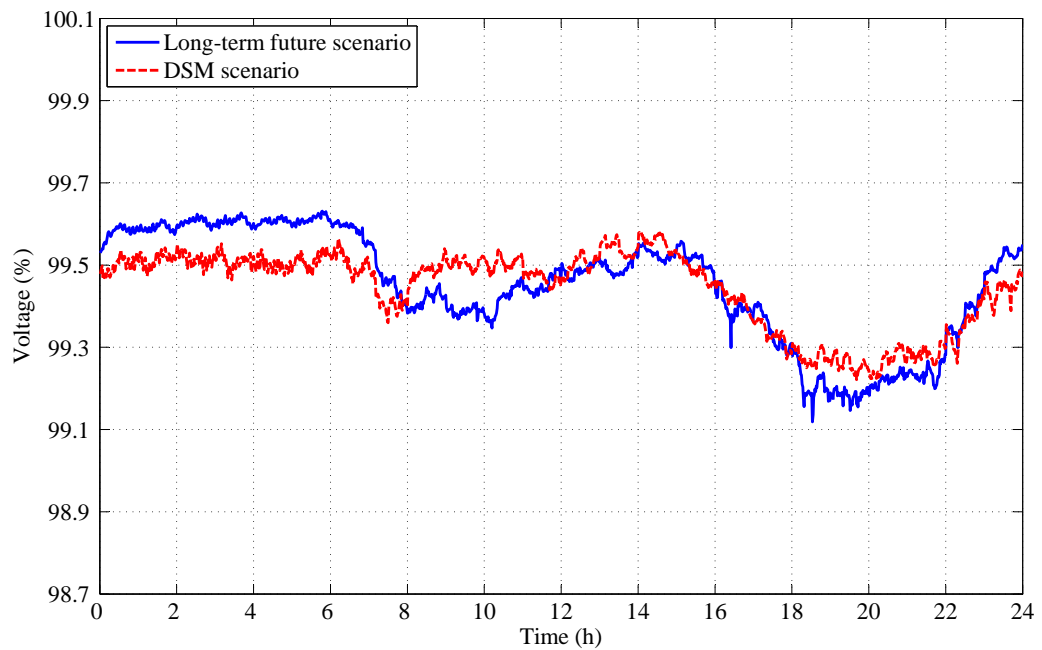
**Figure 5.15:** Average active power demand of highly urban network for long-term future before and after implementation of DSM.

A more interesting result appears on the voltage of the main node right after the transformer in Figure 5.17. Although a drop of 0.1% arises during the night compared to the long-term future scenario, it is noticeable that the voltage level is approximately stable up to around 15:00, and the voltage drop during the day has reduced because of the reduced demand.

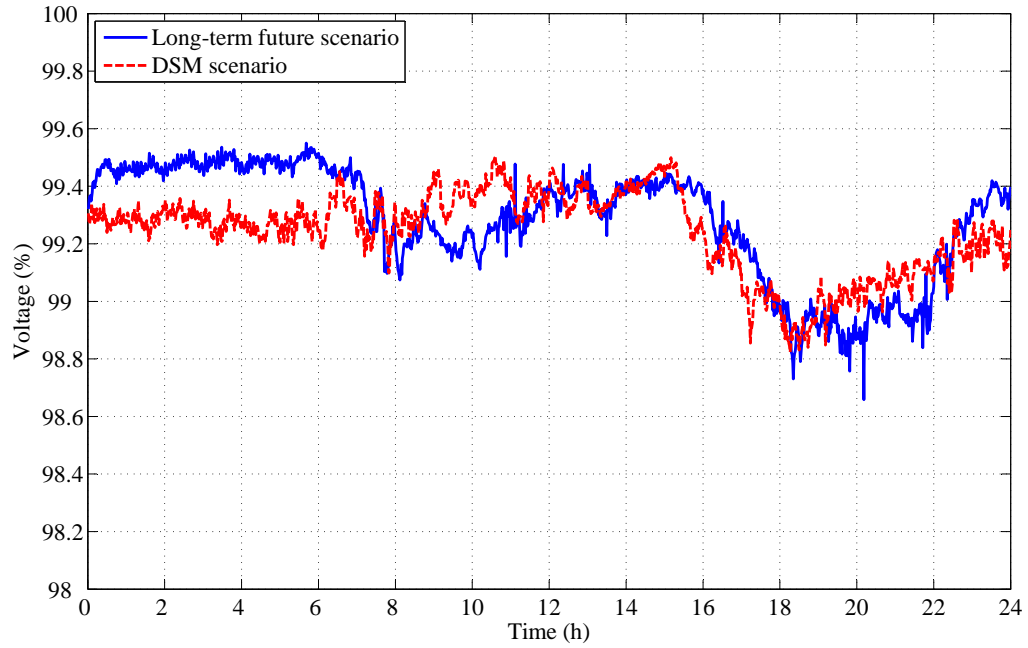
Similar result is appeared in the voltage response at the most distant node (Fig, 5.18).



**Figure 5.16:** Average reactive power demand of highly urban network for long-term future before and after implementation of DSM.



**Figure 5.17:** Average voltage variation of highly urban network at the transformer for long-term future before and after implementation of DSM.



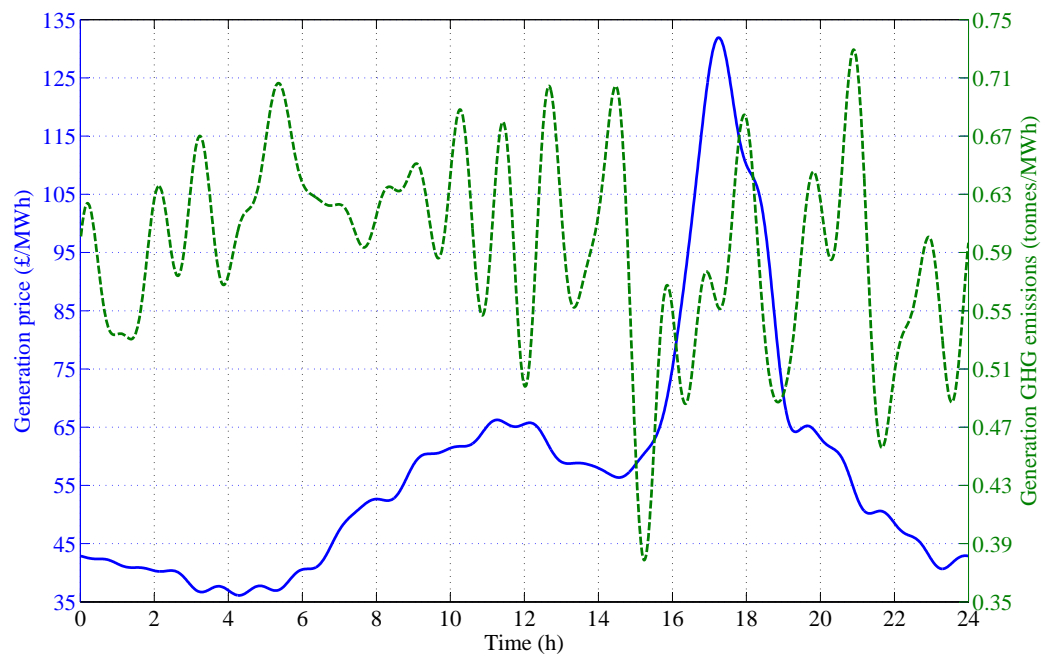
**Figure 5.18:** Average voltage variation at the most distant node of highly urban network for long-term future before and after implementation of DSM.

## 5.6 Seasonal effect

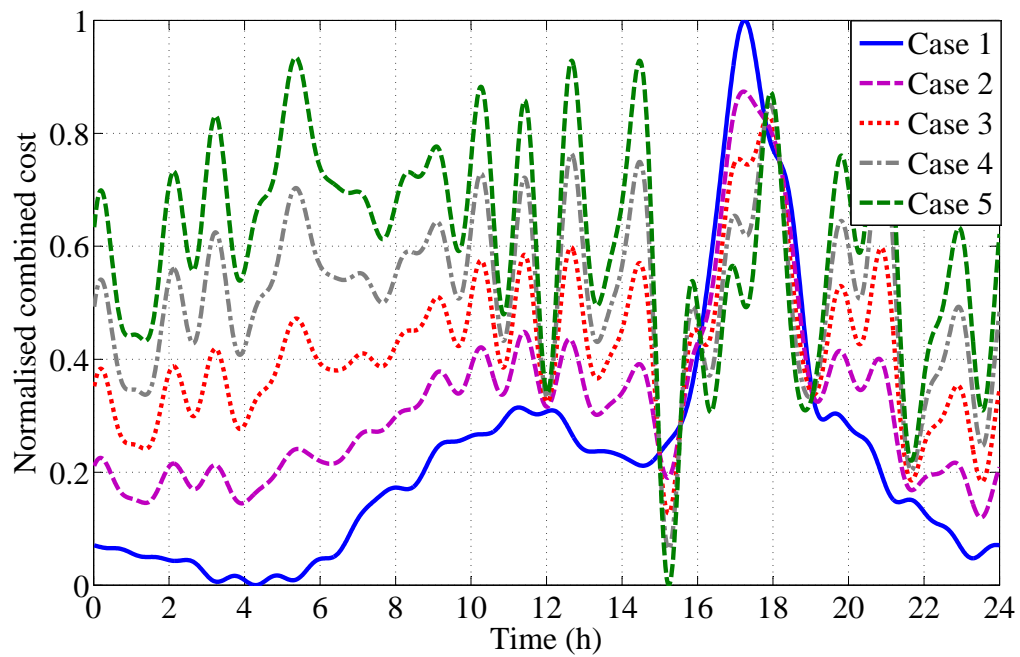
This study was conducted based on the profiles of the price and GHG emissions during the winter of 2012/2013. However, these profiles are very sensitive to the changes in the generation mixture which is strongly correlated to the season and the price of fuel.

### 5.6.1 Different generation mixture

The winter of 2008/2009 was selected in order to study the sensitivity of the DSM implementation in different profiles. Between the two winter periods of 2008/2009 and 2012/2013, the introduction of fracking and its increased use in the extraction of gas resulted in the change of fuel prices and the generation mixture. These changes affected the profiles of price and GHG emissions (Figure 5.19) and subsequently the combined cost (Figure 5.20).



**Figure 5.19:** Daily profiles of price and GHG emissions per MWh [73, 133] for the winter of 2008/2009.



**Figure 5.20:** Normalised combined cost profile for each case according to Eq. (5.1).

### 5.6.2 Results

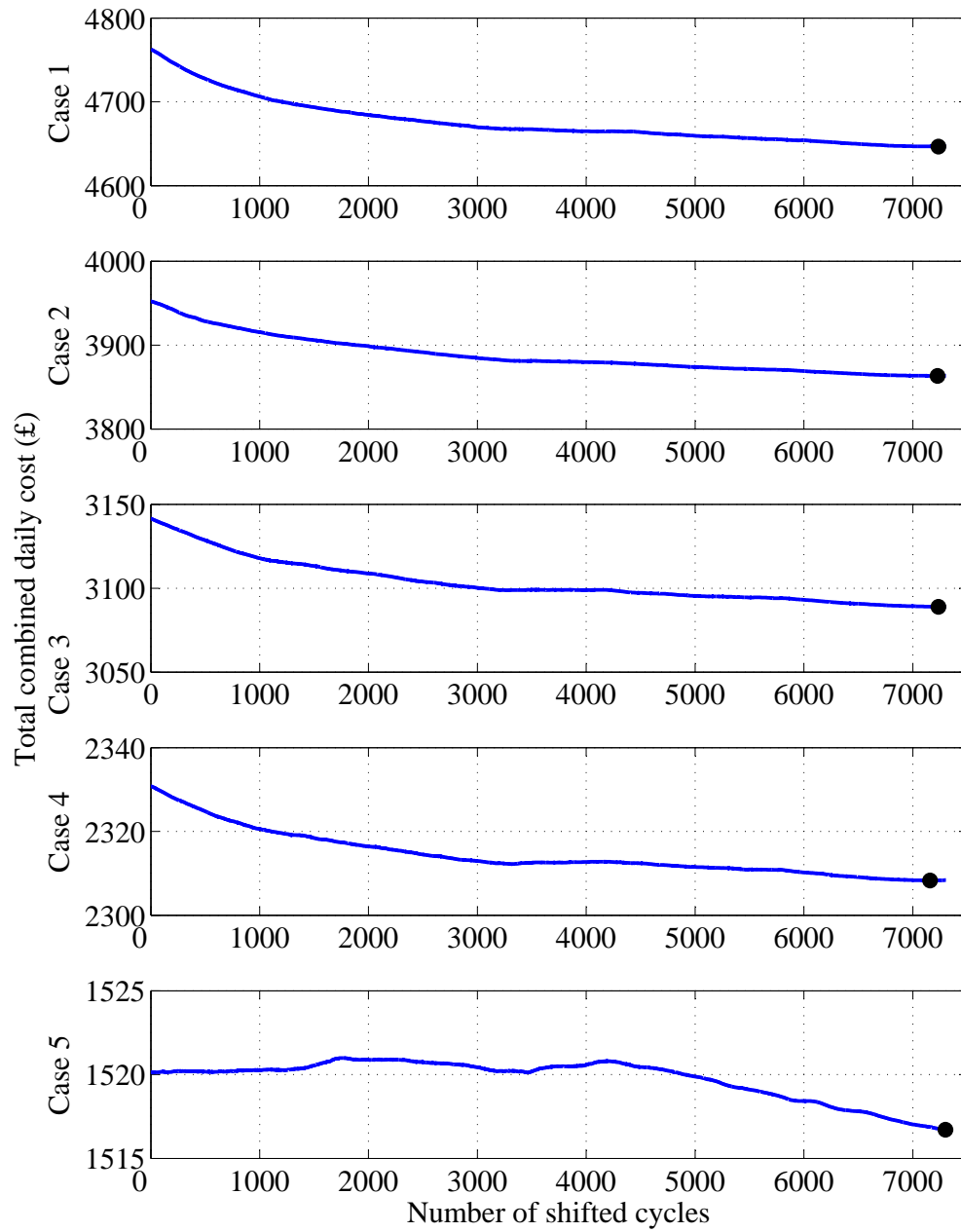
The profiles from winter of 2008/2009 enable opportunities for a greater reduction in the combined cost. The most interesting effect is on case 5 when the algorithm is based exclusively on GHG emissions. It seems that the more shifted cycles are done the more GHG emissions are decreased.

In respect of the GHG emissions, the different effect of DSM actions is noticeable during the two winter periods. The fact that GHG emissions are barely reduced because of the DSM actions can also be seen in Table 5.4. In winter of 2008/2009, the emissions increase at the beginning in cases 1 to 3 while they are more constant for cases 4 and 5 where the GHG emissions profile outweigh the price profile. Then, after approximately 4500 shifted cycles, the emissions reduce to their minimum values. On the other hand, the GHG emissions profiles allow for further reduction by taking advantage of all the available load shiftings. This response is completely different from winter of 2012/2013 where GHG emissions are increasing.

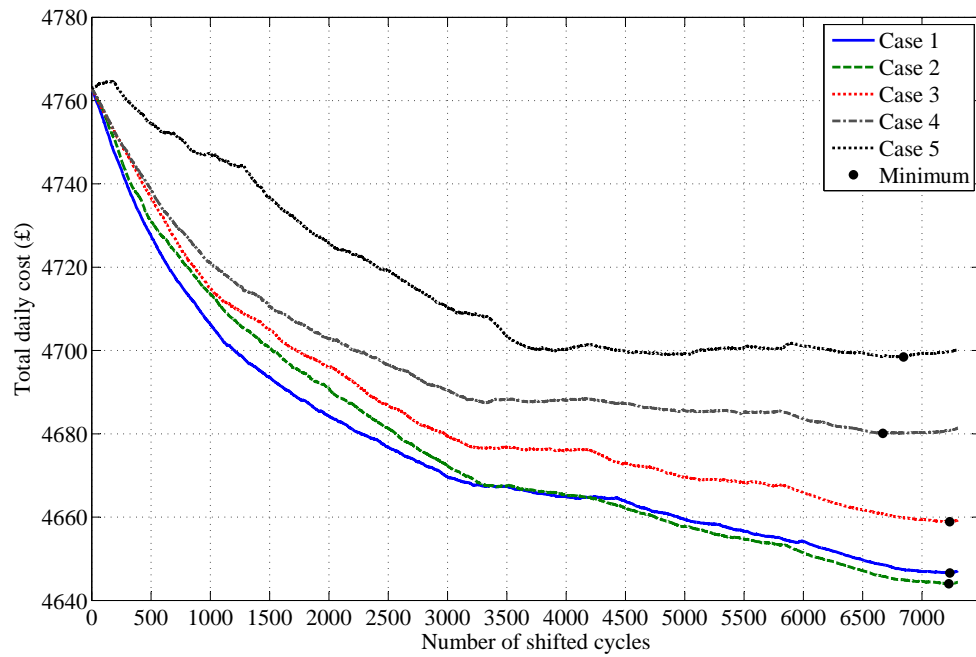
**Table 5.4:** Savings among test cases for winter 2008/2009

Test Case	Total combined cost savings	Total cost savings	Total GHG emissions savings	Cost of power demand
Case 1	2.4%	2.4%		1.8%
Case 2	2.3%	2.5%	<0.01%	1.9%
Case 3	1.7%	2.2%	0.1%	1.7%
Case 4	1.0%	1.7%	0.2%	1.4%
Case 5	0.2%	1.4%	0.2%	1.1%

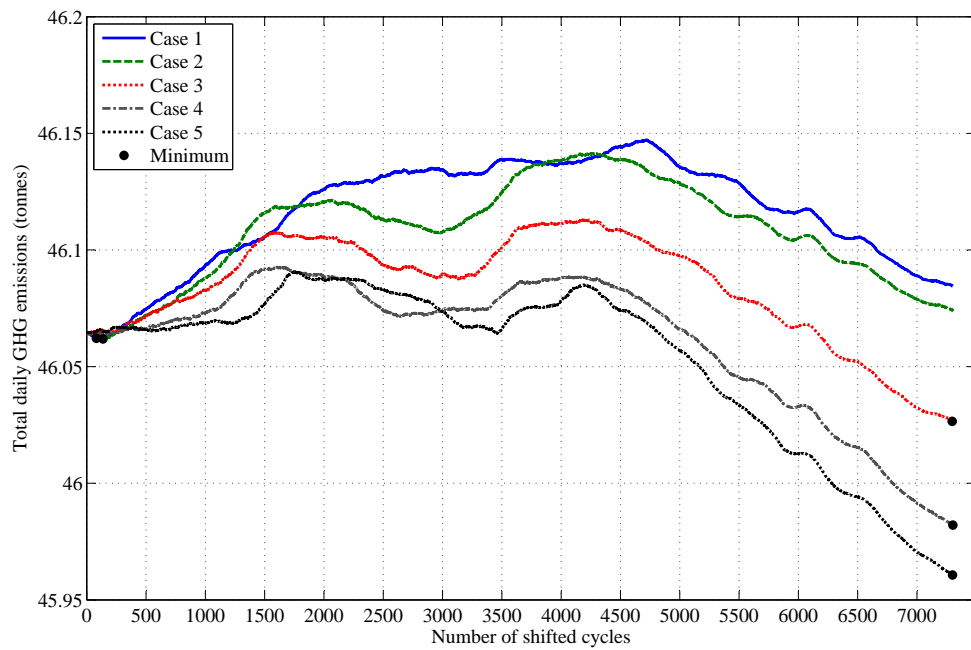




**Figure 5.21:** Effect of DSM algorithm on total combined cost.



**Figure 5.22:** Differentiation of cost due to price according to the number of load shiftings for each case.



**Figure 5.23:** Differentiation of GHG emissions according to the number of load shiftings for each case.

## 5.7 Conclusion

In this chapter, a methodology for the implementation of DSM that takes into account the minimisation of the cost of the power demand and the GHG emissions was presented. This method is highly dependant on the time of day and the year of the analysis as the profiles vary significantly due to factors that impact the generation process. The results show that the financial factor has a greater impact in shaping the combined total cost, suggesting that it is more difficult to achieve GHG emissions savings than cost reductions by shifting residential load. This may explain the current situation of generation, where price is the main objective and GHG emissions reductions are difficult. From the load modelling point of view, the ability of the model in identifying small variations and how sensitive it is, is shown in the results. This advantage of the model allows for more detailed presentation of the problem and, thus, studying more options for a better solution. For example, local load management to address this issue or application of this methodology on different load category according to the customers' needs, could be some of the available options.

It should also be noted, the change in the profiles and the generation mixture after the fall in coal prices, mostly as a result of increased fracking in the USA, had a substantial impact on the potential savings in cost and GHG emissions. The contradictive profiles that occurred, caused increase in GHG emissions after an extensive application of the DSM actions. This highlights the necessity of using detailed power demand profiles and the difficulty of forecasting the impact of DSM actions without considering up-to-date cost and emissions profiles.

It was also shown how the load demand affects the network after the implementation of DSM by considering a network analysis of a highly urban network. The key conclusion lies on the modification of the active and reactive power coefficient. In the future, the load mixture and associated electrical characteristics will be different and the forecast for the values of  $n_p$  and  $n_q$  is not straightforward without independent study of each load category.

# Conservation Voltage Reduction

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## 6.1 Introduction

This chapter presents the study on the benefits and barriers of optimising the supplied voltage to maximise the efficiency of the operation of an electrical network. This technique is widely known as Conservation Voltage Reduction (CVR) and utilities have been studying this option for more than 30 years [91]. As previously mentioned in Chapter 2, research has proven that a 1% reduction in nominal voltage can result in approximately a 1% decrease in power demand.

The research presented here investigates this method from a different perspective, using the developed load models and the detailed representation of the variation of the coefficients of the power demand. A stochastic simulation approach is utilised to quantify the changes in demand reduction for different network/load configurations during the day for 3% supply voltage reductions. This was implemented into two stages:

1. The voltage reduction was applied during the whole day in order to present the effect of the variation of the coefficients of the polynomial power model. This also set the limits on the possible savings that can be achieved by this technique.
2. A control algorithm was developed to focus on the time intervals of interest, such as the peak hours, to study the impact of a realistic implementation of CVR.

In the second stage, two cases are included: the use of CVR as an independent scheme for the reduction of energy demand and the use of CVR as an auxiliary measure to maximise the benefit of DSM application. In addition to the recorded active/reactive power reduction, the impact on the efficiency, i.e. losses, and the voltage profiles within the LV network will be also considered.

This work was implemented in identified sectors of LV residential highly urban networks that currently are not controllable. Although the secondary distribution transformer (11/0.4 kV) does not include voltage control functionality (beyond manual tap changes for seasonal demand variations), it is assumed that the voltage on the primary winding can be controlled by manually adjusting the system impedance of the infeder, to represent staged voltage drop actions. This can be achieved as the primary distribution transformers (33/11 kV) are equipped with various devices for voltage control, such as static VAR units or on-load tap-changers

(OLTC) transformers.

## 6.2 Power reduction through voltage control

The CVR scheme is based on the voltage dependence of the actual drawn power of an electrical load. As described in Chapter 2, a difference between the supplied and rated voltage can cause a variation in the actual power that a load requires for its operation. The CVR strategy takes advantage of this characteristic to manipulate the total energy consumed by realistic load by reducing the supplied voltage by a small percentage.

In order to set the maximum potential savings from a supplied voltage reduction, a hypothetical scenario was developed in which 26 groups of 380 residential power load profiles were developed and used to populate an LV residential network. The supplied voltage level was reduced by 3% during the whole day without any control algorithm to identify the effect of this technique on the load and the time intervals where the effect is maximised.

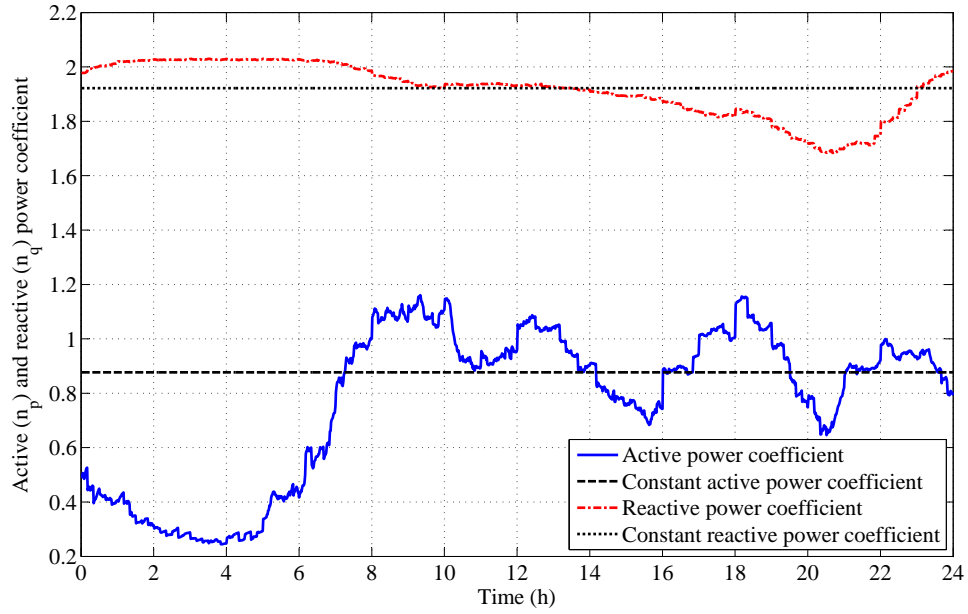
It can be seen from the power load models in Chapter 2, that the values of the polynomial (or alternatively the exponential) coefficients of active and reactive power that define an electrical load have a significant role on the result that can be achieved via voltage regulation. Figure 6.1 presents the average active,  $n_p$ , and reactive,  $n_q$ , power coefficients of the residential profiles used. The weighted mean daily values of these coefficients profiles are also presented here and were calculated from the product of coefficient, e.g.  $Z_p$ , and rated power  $P_0$  at time  $t$  for household  $h$ , over the total power demand at the same time step  $t$  (6.1).

$$\begin{bmatrix} Z_{p,q,mean} \\ I_{p,q,mean} \\ P_{p,q,mean} \end{bmatrix} = \begin{bmatrix} Z_{p,q}^{ht} \\ I_{p,q}^{ht} \\ P_{p,q}^{ht} \end{bmatrix} \frac{\begin{bmatrix} P_0^{ht} \\ Q_0^{ht} \end{bmatrix}}{\sum_{i=1}^N \begin{bmatrix} P_0^{it} \\ Q_0^{it} \end{bmatrix}}, \quad \begin{matrix} t \in [1, T] \\ k \in [1, N] \end{matrix} \quad (6.1)$$

where:  $P_0$  and  $Q_0$  are the nominal/rated values of active and reactive power,  $Z_p$ ,  $I_p$ ,  $P_p$  and  $Z_Q$ ,  $I_Q$ ,  $P_Q$  are the polynomial/ZIP model coefficients of active and reactive power,  $T$  is the total number of time steps and  $N$  is the number of customers/customers group.

The resulting weighted mean value confirms the general aggregate characteristics of the LV load: close to constant current for active power, with reactive power approximating a constant impedance load type. The weighted mean values are shown in Table 6.1.

Figure 6.2 presents the average variation of the percentage of active and reactive power reduction during the day. It can be seen that the power reduction percentage is following the  $n_p$  and  $n_q$  curves and the greater power saving occurs during the peak hours. In detail, the active power reduction varies between 0.8-2% during the night-time and 3-4% during the day and at peak



**Figure 6.1:** The average profile and daily average value of the active and reactive power coefficients for 10,000 UK residential customers.

**Table 6.1:** Weighted mean of power model coefficients

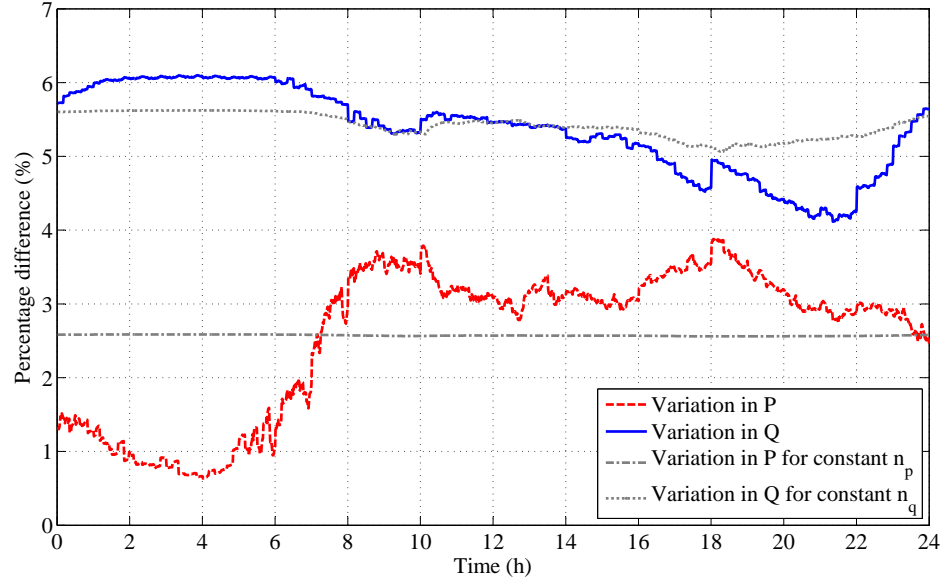
Exponential		Polynomial					
$n_p$	$n_q$	$Z_P$	$I_P$	$P_P$	$Z_Q$	$I_Q$	$P_Q$
0.8766	1.9219	0.4001	0.0763	0.5235	1.0419	-0.5804	0.3208

hours. It is obvious that the voltage reduction has a greater effect on the reactive power due to the higher absolute values of the exponential load model parameter. The reduction of reactive power demand can reach around 6% during the night and 5.5% during the day. However, note that the reactive power reduction is slightly over 4% during the night peak time. Regarding the operation of the network, a negligible reduction of about 1% was noticed in total network losses.

The comparison between the detailed values and the constant values of weighted mean value polynomial model, shows the advantages of using the daily detailed load models. When using the constant values of weighted mean value polynomial model, the percentage reduction of power demand remains approximately constant during the day. Therefore, this will over-estimate the reduction of active power demand during the night-time and underestimate the reduction during the peak hours, which are of most significance. The opposite result occurs for the case of reactive power, where the use of daily weighted mean value will cause an underestimation of the result during the night and over-estimation during the night peak hours.

The change in duration curves of both active and reactive power demand, before and after the

voltage reduction, are shown in Figures 6.3 and 6.4. As it can be seen, the reduction of active power demand is more obvious at the peak hours while the effect of the voltage reduction on reactive power demand is observable during the whole day. These results confirm the intention of focusing the voltage regulation during the peak hours by implementing a control algorithm.



**Figure 6.2:** The percentage savings of active and reactive power demand for reducing the supplied voltage by 3%.

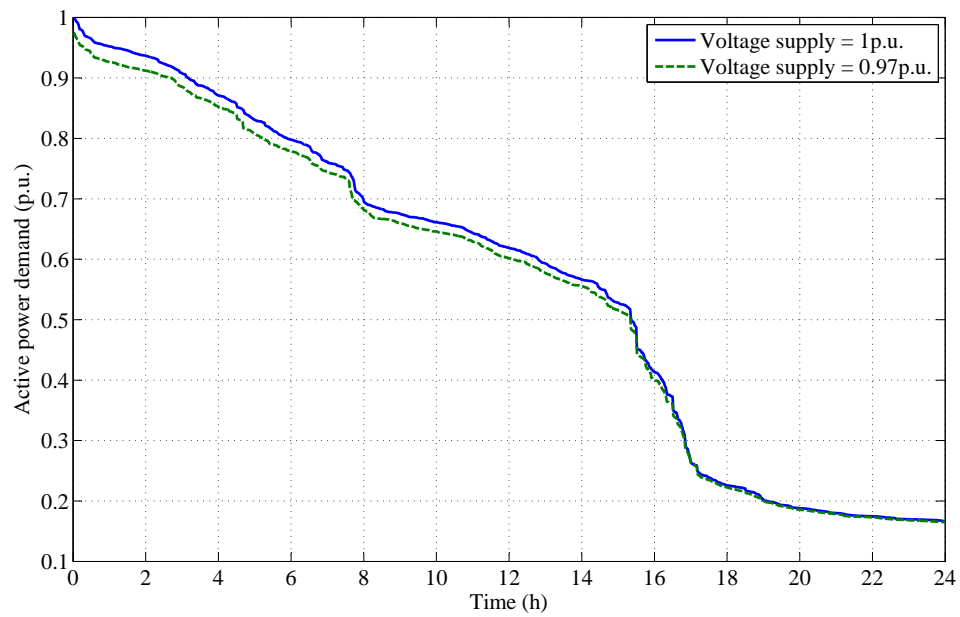
## 6.3 Control of supplied voltage

### 6.3.1 Methodology

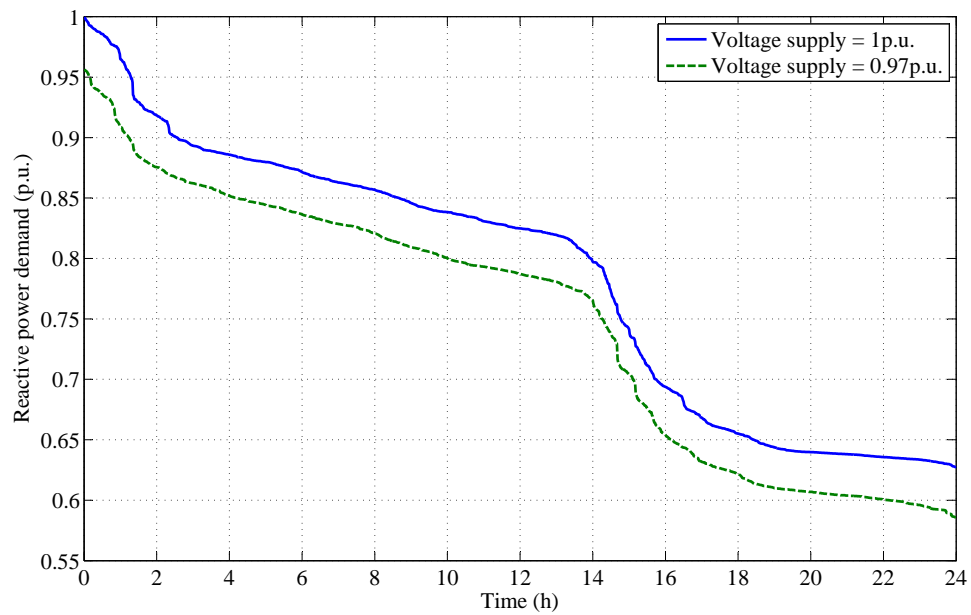
This study was based on the utilisation of the detailed characteristics of the developed LV residential load profiles which are given by the developed tool that is described in Chapter 3. Furthermore, there were some assumptions that had to be made regarding the installed network equipment in order to implement the proposed methodology. These characteristics of the study are presented in this section and the algorithm for controlling the voltage is described.

The implementation algorithm does not differentiate a lot from the algorithm used in Chapters 4 and 5 for the network analysis. The residential load profiles are proportionally and randomly allocated in the highly urban network in order to have a balanced loading among the three phases. The new section of the code is where the supplied voltage is controlled at each time step. The control process is divided into three steps:

1. Setting of the limit at the current loading of the transformer.



**Figure 6.3:** The duration curve of the active power demand before and after reducing the supplied voltage by 3%.



**Figure 6.4:** The duration curve of the reactive power demand before and after reducing the supplied voltage by 3%.

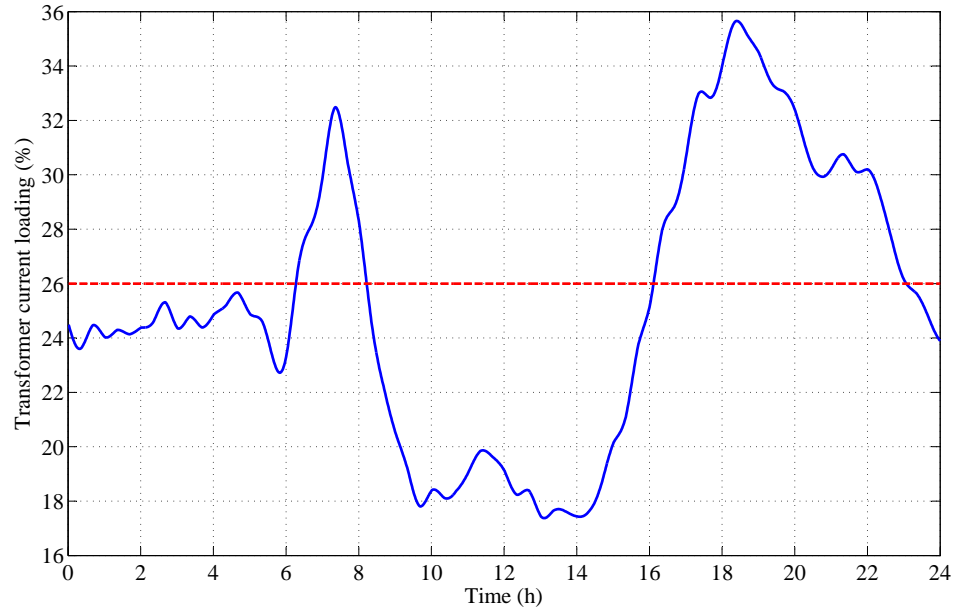
2. Check whether voltage reduction is possible and is required.
3. Adjustment of the level of supplied voltage.



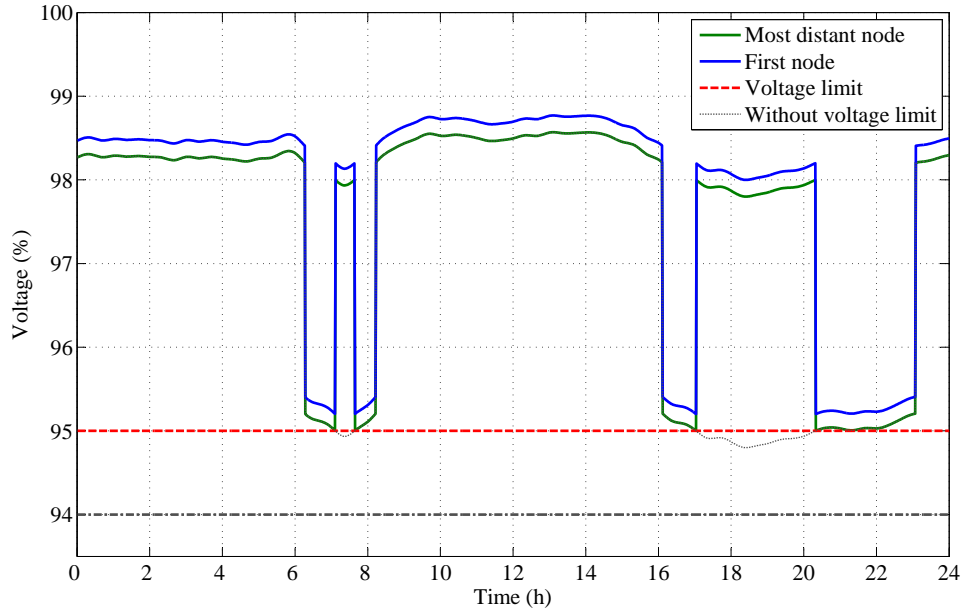
The driver of the voltage control is the current loading of the transformer (TIL) at each phase so it has to be set at the beginning. The current loading is the immediate effect of the total power demand at each time step and it is easily measured. Normally, the secondary LV transformer operates close to 35% of the rated current loading per phase during the day [134].

At each time step, the TIL of all phases are monitored and compared against the set limit after the power flow calculation. A counter is used to measure the instances when the TIL of at least one phase is higher than the limit. However, the voltage level has to remain between the allowed limits in the whole network, highlighting the need for monitoring of the voltage level of all the nodes. In order to avoid stressing the network, particularly during the time of peak demand, the lower voltage limit has been adjusted to 1% higher than the nominal one, thus -5% instead of -6%. In case that the voltage at any node is decreased lower than this limit, the counter decreases by one.

Although the TIL is checked at every time step, the supplied voltage is adjusted less frequently. It is assumed that the reaction time of the actuator is minimum 5 minutes. At the last step, the decision is taken according to the value of the counter. Figures 6.5 and 6.6 show how the algorithm works. In Figure 6.6, it can also be seen what the voltage profile would be without delimiting the lower allowed voltage level.



**Figure 6.5:** An example of the current loading of a transformer compared with a set limit for applying voltage control.



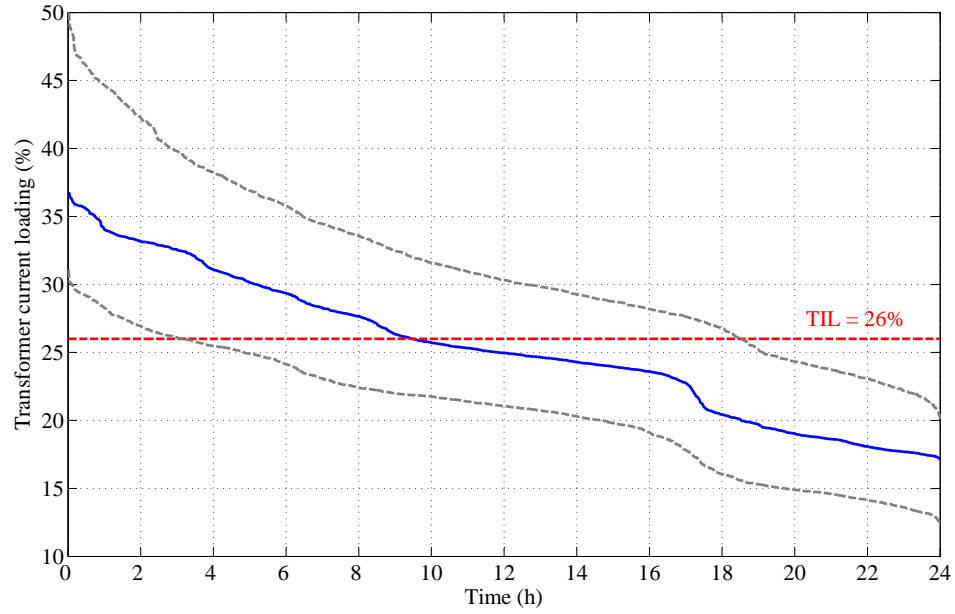
**Figure 6.6:** The voltage profile of the first and the most distant nodes in a LV HU network.

### 6.3.2 Implementation

This section illustrates how the methodology outlined in the previous section is implemented using the typical UK LV network for highly-urban areas, which was described in Chapter 4. The detailed power profiles for 26 groups of 380 residential customers were developed, using the tool described in Chapter 3, to populate the network.

Figure 6.7 presents the duration curve of the average, blue solid line, TIL per phase that derives from the network analysis of the above groups of customers before applying the voltage control methodology. The wide envelope, gray dashed line, justifies the need for the large number of groups to acquire more objective and unbiased results. For this case study, the TIL threshold was set at 26% since almost 37.5% of the time the transformer operated over that level, increasing the effect of this action on the reduction of the daily energy demand.

Two scenarios have been created to study the impact of controlling the supplied voltage on the total energy demand. The first one includes the developed demand profiles before implementing any DSM actions in order to investigate the potential benefit of implementing this technique in the near future. The second scenario investigates the effect of voltage control as a supplementary action to the DSM to maximise the reduction of the daily energy demand and power demand during the peak hours.

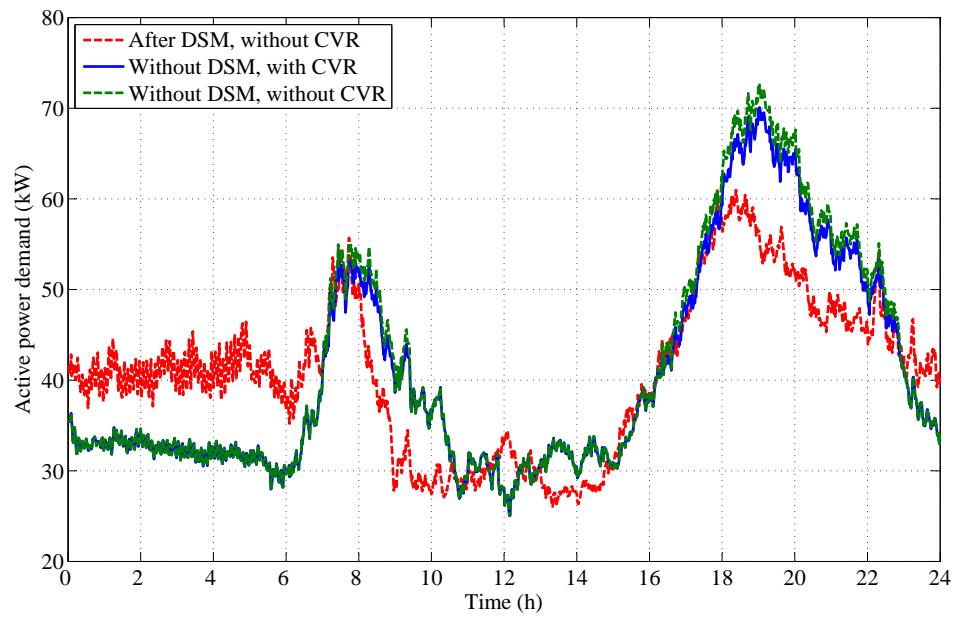


**Figure 6.7:** Duration curve of the average current loading of the simulated transformer.

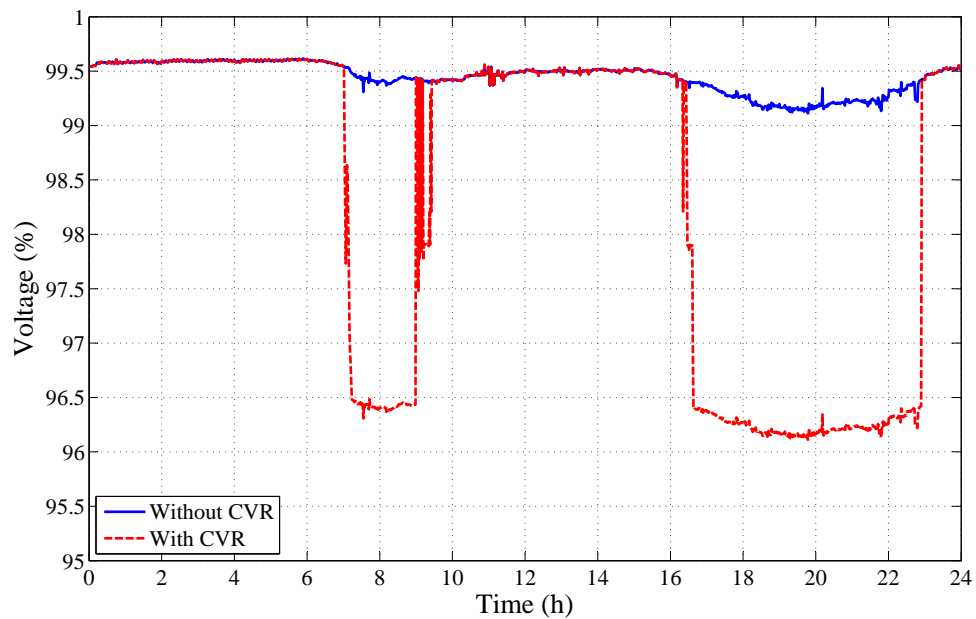
### 6.3.2.1 Independent scheme for daily energy consumption

The advantage of the application of the CVR technique is that it can be applied faster than DSM and, thus, be used as an short-term alternative in the attempt to manipulate the daily load demand curve without disruptions in customers' life. There is no immediate need for technical upgrade of the network, since the voltage that is supplied in low level distribution networks could be controlled in higher voltage level substations which are equipped with the appropriate equipment, such as OLTC transformers. However, the installation of similar equipment locally can be done faster and cheaper than the required network upgrade that would allow for the implementation of DSM, such as installation of monitoring and activating devices to the network and metering equipment to the customers along with the necessary communication and control network.

In this scenario, the CVR methodology was applied to the demand profiles of the short-term future case. The regulation of the supply voltage can reduce the peak demand as it was shown in the previous sections. The maximum reduction achieved was 3.9% and 3.5% during the evening and morning peak respectfully. Although this reduction is significant taking into account the required interventions, they cannot be compared to the results from DSM implementation. As it can be seen in Figure 6.8, the difference of the effectiveness of the two techniques is greater at evening peak where the DSM actions are more determinant. On the other hand, the total daily energy was reduced by approximately 1.5%, while the DSM actions do not affect it at all by default.



**Figure 6.8:** Comparison of the active power demand variation between the implementation of DSM and CVR.



**Figure 6.9:** The voltage profile of the most distant nodes in the LV HU network with and without CVR before the implementation of DSM.

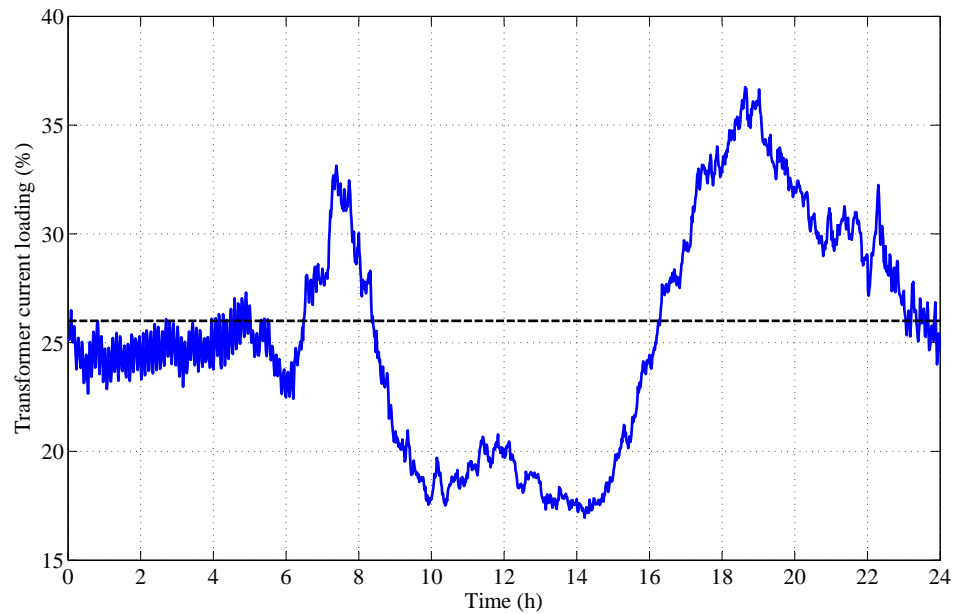
Despite the application advantages described above, there are some significant disadvantages in the response of the network. The largest drawback is the very low resulted voltage at the

most distant node of the network which can get to about 95.5% on average (Figure 6.9). The low voltage level is close to the lower allowed voltage level at 94% and, considering that the CVR is enabled for approximately 37.5% of the time, the possibility of breaking this limit and introducing voltage stability and supply quality issues cannot be excluded.

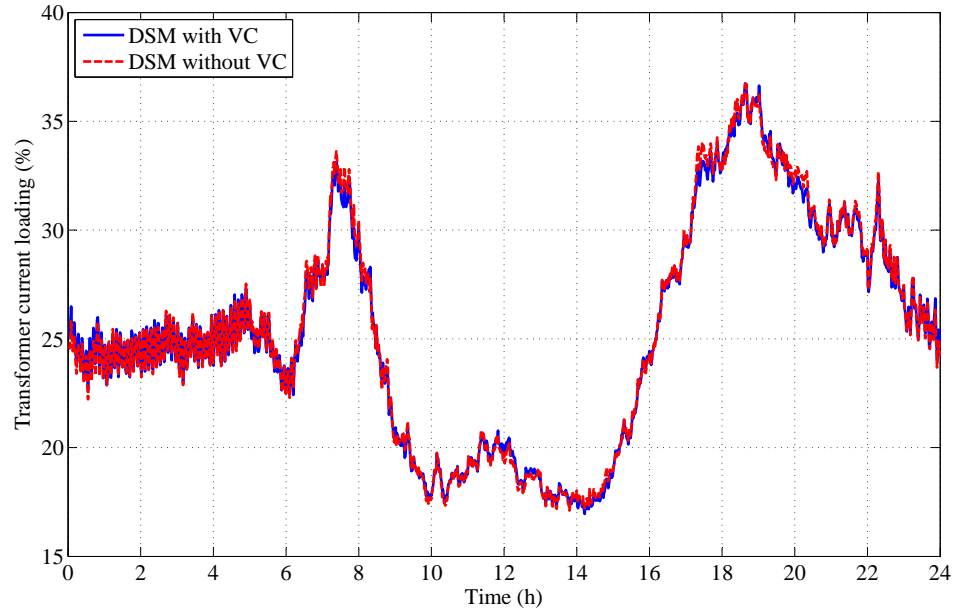
### 6.3.2.2 Supplementary scheme for DSM

The implementation of CVR, which affects mainly the peak hours of the day, can be used as a complementary measure to increase the effectiveness of DSM at these periods. In the following study, the CVR methodology was applied on the scenario of the long-term future load with DSM to assess the arising benefits and disadvantages.

The threshold of the current loading of the transformer has been set at 26% (Figure 6.10), as discussed in the previous section. This means that this scheme will affect mostly the morning peak, between 6am and 8am, and the evening peak, between 4pm and midnight. It can also be seen in Figure 6.10 that during night, the average TIL is very close to the threshold. This means that, according to each individual simulation, the CVR is also applied in this period. Figure 6.11 shows the minimal change of the TIL after the CVR implementation, due to the limited effect on the total load of the network. Furthermore, note in this figure that there is some slight decrease of TIL during the night. This is a result of the changes in active and reactive power demand and will be discussed later.



**Figure 6.10:** The average current loading of the transformer in a LV HU network and the set threshold at 26%.

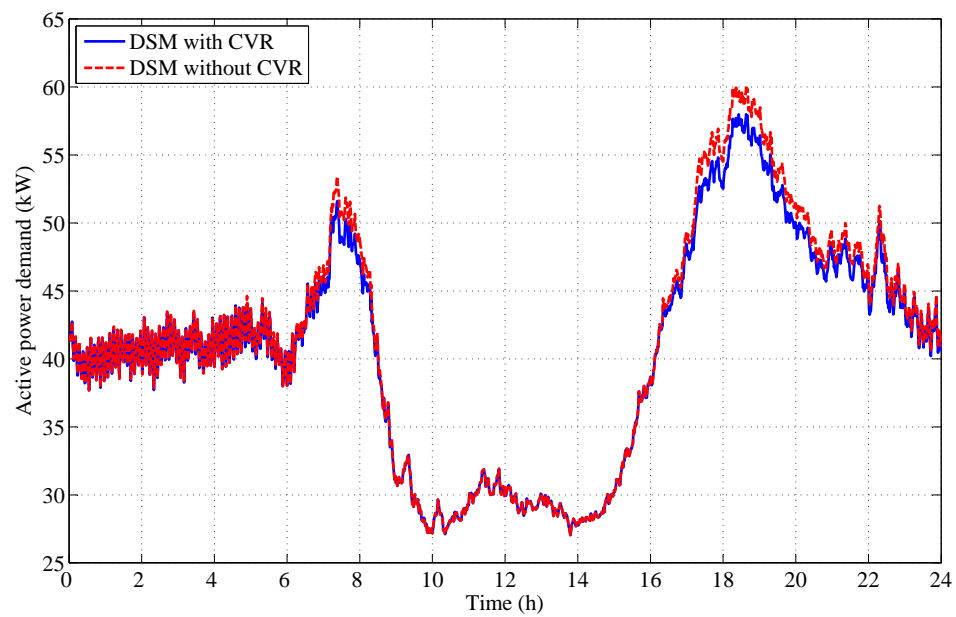


**Figure 6.11:** The average current loading of the transformer before and after the CVR implementation.

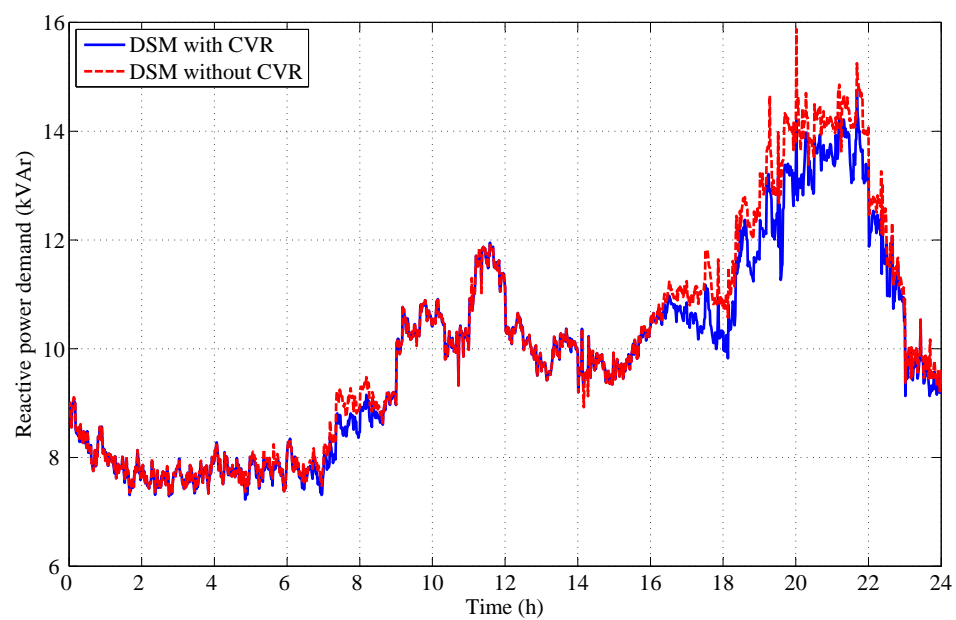
The effect of CVR on active and reactive power demand is demonstrated in Figure 6.12 and 6.13, while Figure 6.14 shows the percentage savings in active and reactive power after the application of CVR. The mitigation of active power demand during peak hours is similar to the first case studied, since the power demand during evening and morning is up to 3.8% less due to the voltage regulation. This can be explained by the fact that the daily profiles of  $n_p$  of long and short-term future scenarios, which affects the most the result of this methodology, are similar, see Section 4.3.

Regarding the total daily energy reduction, although it is at similar level in percentage to the previous scenario but still less (1.2%), it is equal in actual values (973 kWh for CVR after DSM applied on long-term future scenario demand and 976 kWh for CVR on short-term future scenario). This means that the existing difference between the long and short-term future scenario is covered by the implementation of CVR.

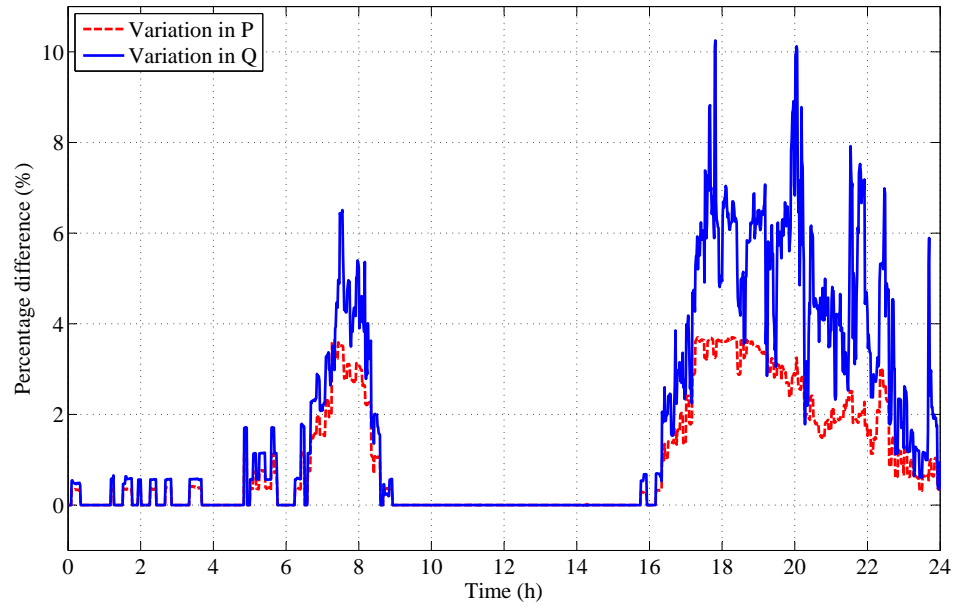
On the other hand, reactive power demand faces greater reductions that reach up to 10% at evening and approximately 7% during morning peak according to Figure 6.14. This significant difference from both the base case and short-term future scenarios derives from the difference in  $n_q$  that was noticed after the load modification (Figure 4.12). This result has also affects the network losses, which are reduced by 2% in total during the 24 hours.



**Figure 6.12:** The active power demand when CVR is applied.



**Figure 6.13:** The reactive power demand when CVR is applied.

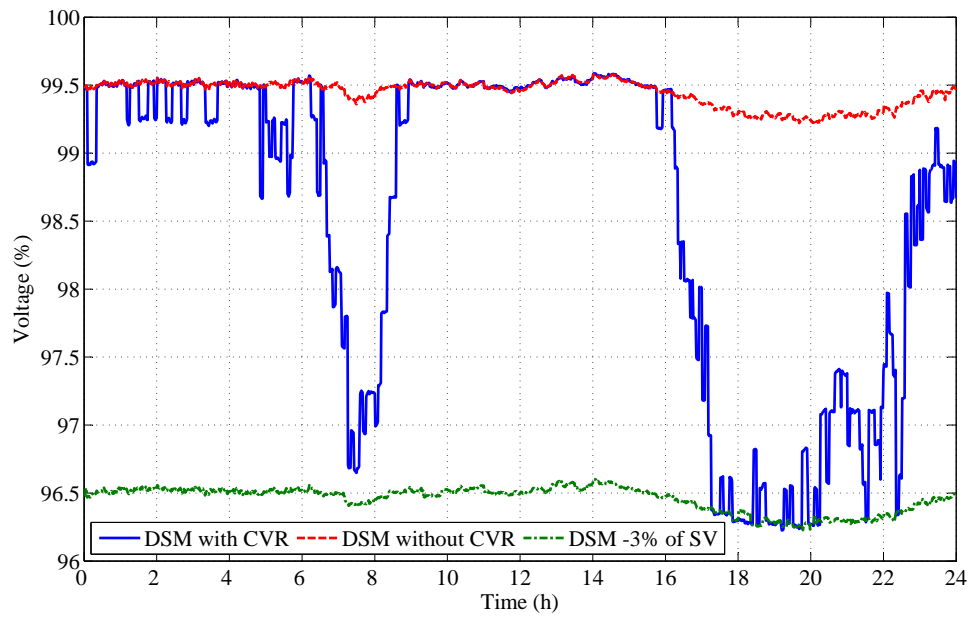


**Figure 6.14:** The percentage savings of active and reactive power demand when CVR is applied.

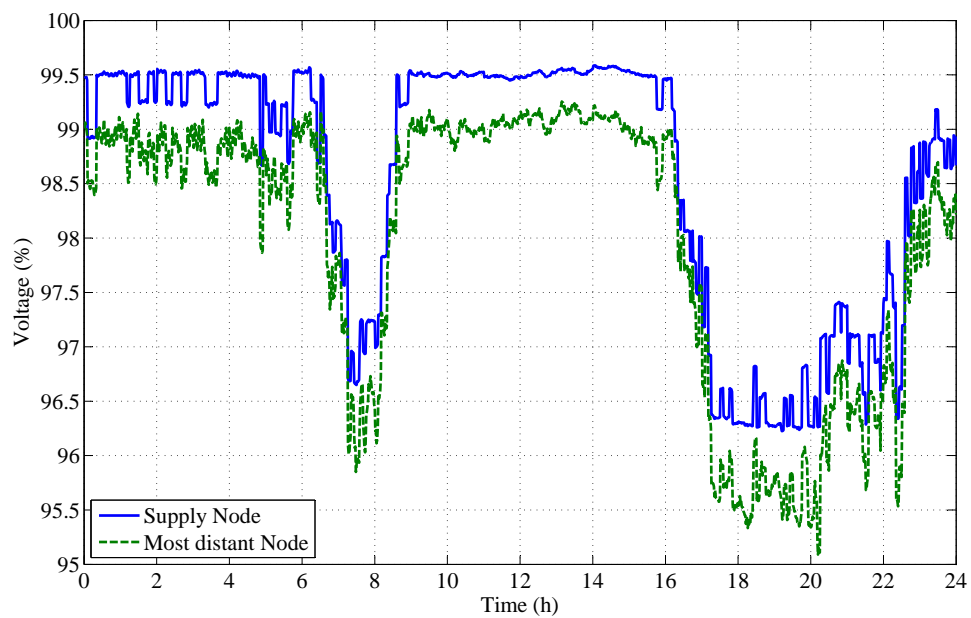
The voltage profile has the expected interaction after the CVR introduction as Figure 6.15 shows. In this case, voltage reductions occur also at night and for wider period at evening, because of the higher power demand during the night due to the DSM actions and the shifted load. This can be noticed by the fact that the voltage was stepped down for approximately 53% of the time. Furthermore, it should be noted that, although the voltage is not reduced in steps, the voltage profile seems to do so. The calculation of the average voltage profile and the large variation in the between the profiles of the simulations give this result. Essentially, it could function as the probability of enabling the control process.

As for the voltage profile in the most distant node in the typical LV highly-urban network, Figure 6.16 presents that it remains too low (95%) despite the reduced load demand that resulted by the implementation of DSM actions. This conclusion suggests that the CVR technique will downgrade the power quality of the network because of the wide and continuous variation of the supplied voltage level.





**Figure 6.15:** The voltage profile of the first node in base case and after the application of both controlled and uncontrolled CVR.



**Figure 6.16:** The voltage profile of the first and the most distant nodes when CVR is applied.

## 6.4 Conclusion

In this chapter the implementation of the CVR technique was studied as a measure to limit the power demand during the peak hours. Although this concept is discussed for quite a long time, the use of detailed daily power models allows for a more precise calculation of the effect of this scheme on the power demand and the network operation. The presented methodology takes into account the TIL level of the transformer and the minimum voltage level in the decision making process for the voltage control.

Three different ways of implementation were studied for the purposes of this thesis. The first one was the unrealistic scenario of immediate uncontrolled reduction of the supplied voltage during the whole day in order to set the maximum limits of the savings that can be achieved. The second one was the implementation of CVR technique onto the short-term future power demand which pointed out the possibility of using this method as an individual scheme for power demand reduction at peak times and the total daily energy. The third case was the use of the CVR method along with DSM actions to maximise the benefit allowing for more extensive control of the supplied voltage level.

The results of this study suggest that, in general, this method contributes significantly in the power demand limitation considering the low requirements for new network equipment and capital investment. However, the large voltage variation and the low levels of the voltage (close to the low limit of the network voltage level) decrease the quality of the network operation. Furthermore, the presented results enhances the argument for the benefits of a possible overall reduction of the nominal supply voltage.

# Conclusions and Further Work

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### 7.1 Thesis summary

This thesis presented an assessment of the impact of possible future alterations in the mixture of the UK residential load on the operation of the LV network through a number of demand and network management techniques.

Chapter 2 includes an overview of the existing literature on the main topics of this study, highlighting the areas that require improvement or investigation from a different point of view. Although significant attention has been paid on the improvement of load modelling and forecasting for power flow studies, there are no satisfactory datasets or tools to provide detailed load models that would allow for more precise network studies.

The literature review also included research on DSM techniques showing that the majority of the studies are either performed at high voltage level or focused only on specific loads that are conveniently flexible in use and management. Also, the motivation for the research is usually the manipulation of the power demand profile from the generation and transmission point of view, while the customers point of view, in terms of comfort, economic or environmental costs, is a byproduct of the study or ignored completely. Furthermore, research regarding the control of a secondary LV transformer voltage supply is reviewed as an additional network management method. The lack of information on the electrical characteristics of the aggregated residential loads leads to a limited investigation of any potential benefits and is addressed in this research.

A novel bottom-up methodology for developing detailed residential power profiles that describe the electrical characteristics of the loads is presented in Chapter 3. Activity profiles of domestic customers are created by a Monte Carlo-Markov chains modelling technique and then combined with appliances that are selected based on UK usage statistics from a database of the available appliances that populate UK households to develop representative load profiles of the UK population. An additional database of the UK average ambient conditions, e.g. solar irradiance and temperature, is used for a more accurate modelling of some loads such as lighting and heating. Afterwards, the electrical characteristics of each selected appliance are aggregated to calculate the load model of each household. Further aggregation by combining

more households is possible to create large datasets for a number of network studies. The model is verified against existing models and available aggregated measurements.

Chapter 4 considers the possible changes in the load mixture in the coming years and presents the effect they will have on the operation of the grid. The expected alterations and replacements due to the introduction of technologically advanced appliances were divided into two scenarios: near future and distant future scenario. The results were compared with the base case scenario that includes the current appliance mixture. A network analysis was performed for all three scenarios to study their impact on the operation of a LV highly urban typical UK network.

Chapter 5 applies load shifting, one of the main DSM actions, on the developed load profiles using the wet loads, such as washing machines and dishwashers, as an example of the proposed methodology. The financial and environmental benefits to customers are the motivation for this study as the objective of the described optimisation algorithm is to minimise the total daily cost and the GHG emissions that derive from the power demand.

Although many studies model the loads as constant power loads, they are actually dependent on the supplied voltage. Thus, it is possible to reduce the power demand by controlling the voltage level at a secondary LV transformer. The impact of a possible application of this method, either as a short-term solution that could be applied in the existing network or as an additional action to the utilisation of DSM, on the grid is discussed in Chapter 6.

## 7.2 Thesis statement

The original Thesis statement claimed that a bottom-up, user-inclusive domestic electrical load model may yield high-accuracy aggregated demand profiles. Comparing the results from using this model, with the existing literature, proved that this part of the Thesis statement was correct.

Additionally it was hypothesised that the improved demand model may facilitate detailed technical, economic and environmental assessment of demand side management strategies. In Chapters 4-6 it was shown that the model can indeed be used for a wide range of applications, including demand forecasting, DSM methods assessment and network control strategies assessment. Thus, the second part of the original Thesis statement also stands true.

## 7.3 Implications of the research

### 7.3.1 Residential load modelling method

The representation of residential demand is principally connected to the behaviour and activities of the customers. Thus, the MCMC method was used in this study to generate activity profiles that reflect the UK population taking into account the different types of customers and the different way they use the residential appliances. The MCMC method allows to overcome this diversity and develop trustworthy power demand load models.

The power demand profiles that are provided by the publicly available load modelling tool [7, 97] can be useful in a large variety of applications and network studies that require more detailed data. The high correlation between the resulting aggregated profiles and the available data, demonstrate that the tool is reliable and accurate enough to be used in power system studies. The functionality of the developed load models provide information that previously were represented by simplified generic models.

The proposed methodology is temporally and spatially independent. The flexibility and adaptability of the tool derive from the ease with which the databases, that are used here and represent the UK population, can be adjusted to represent the demographic characteristics, activities, ownership and use habits of household appliances of any population for any period of the year. Furthermore, it is important that all this information come from databases that are publicly available; exist for many countries allowing for applying this model to other places; and, although they have been developed for different kind of studies, such as statistics, socio-economic research etc, they can be adapted to the presented modelling framework.

### 7.3.2 Future load replacement and DSM implementation

Regarding the introduction of the advanced technologies in the households and the change in the load mixture, they can be used in the future network studies. The additional information that comes from the shape of the aggregated load model after the replacement assists in the comprehension of the level of the impact of the different appliances and the way the appliances interact with each other and the grid.

For the DSM implementation, from the load modelling point of view, the primary outcome of this study is that it is important to take into account the individual appliances with specific operational cycles when the studies are conducted in LV level. This result enhances the value of the presented load modelling approach. For the results from load shifting point of view, the difficulty of forecasting the impact of DSM actions without considering up-to-date cost and emissions profiles is shown. Furthermore, the results show that the financial factor has a greater impact in shaping the combined total cost, implying that it is more difficult to achieve GHG emissions savings than cost reductions by shifting residential load. This may explain the current

situation of generation, where price is the main objective and GHG emissions reductions are difficult.

### 7.3.3 Voltage control for demand reduction

This application of the detailed load models shows the need for calculating the parameters of the polynomial (or exponential) load model that describe the electrical characteristics of the load. The results show that there was significant underestimation of the savings during the peak hours, when considering the typical generic model coefficients. Although disproportionate variation of the voltage level would have occurred, this finding suggests that the investigated method can be used as an additional measure for reducing the peak power demand with minimal changes in the existing network equipment.

## 7.4 Research Limitations

### 7.4.1 Residential load modelling method

Although the proposed method can achieve relatively highly accurate results, there are some household appliances that could not be modelled. Small electronic devices, such as mobile phone or tablet chargers, were not included in the tool. Regarding the flexibility of the model, the excessive amount of required input data required and the difficulty in acquiring them, decreases the possible locations that this methodology can be applied.

Also, the already large variation in the given power profile of the residential sector between the available validation sources, caused some difficulty in the proper verification of the tool, as discussed in Section 3.7. Furthermore, the lack of information for the values of the household models' coefficients made the direct validation of the results impossible. The results were validated by the assumption that, since each step of the methodology is validated and the individual models of the appliances have been validated through measurements [38], the produced load models are considered to be realistic and representable of the UK residential load.

### 7.4.2 Future load replacement and DSM implementation

Regarding the load modification, some limitations had to be set in the development of the scenarios investigated. In future scenarios, it is assumed that the behaviour of the customers will remain the same excluding the possibility of the rebound effect, i.e. the increase in the number of energy efficient appliances. It is also assumed that the appliances that are not replaced will follow the existing policy in their construction and retain the same electrical characteristics. As the selected scenarios are actually projections of the possible future modifications of the load mixture, it is uncertain whether modern appliances will have the same electrical characteristics

or will evolve further. For example, the characteristics of LED lamps currently vary among the different brands, while it is expected that they will be standardised in the future.

In order to carry out the study on DSM implementation, it was considered that any required action was possible to be accomplished without taking into account any lack of communication and data acquisition/distribution equipment. Thus, it was assumed that the required infrastructure is available and compatible with the desirable DSM actions. Also, the objective of this study is the assessment of the effect of the maximum possible result without studying the motivation for taking these DSM actions or how many actions are required.

### **7.4.3 Voltage control for demand reduction**

As demonstrated in the results, the need for higher savings in the demand suggests it is possible to push the minimum predicted voltage level close to the lower limit of the allowed voltage supply (-6%) during the period of applying the voltage control, i.e. the peak hours. Then, a further reduction of the voltage level due to a possible fault, such as supply shortage, or sudden large load, could affect the reliability and stability of the network operation.

Furthermore, the analysis was performed in an isolated LV HU typical network. The existing transformers in the equivalent physical networks are not able to control the supplied voltage as discussed in Chapter 6. Thus, the voltage is controlled in higher level, where OLTC transformers are present, and it is adjusted to match the required voltage level.

## **7.5 Potential impact of this work**

The modelling methodology presented can be used in load forecast studies, since it could contribute in predicting the future load demand and the changes in the corresponding parameters of the load models. Furthermore, the outcome of the DSM implementation study can be used in financial and environmental impact studies of the management that could affect the process of generation planning. From the network operation point of view, the DSM actions can be applied in conjunction with other methods, e.g. CVR, to maximise the daily energy savings and the reduction of peak demand.

## **7.6 Further work**

### **7.6.1 Residential load modelling method**

The model could be enhanced for future use. For example, there are some future loads, such as EVs that could be added in the model when reliable load models and enough statistical information on their use are available. Some small scale units of distributed generation (DG)

could also be added, since it is expected to be present in future households. The calculation of the total harmonic distortion that is injected in the system should be included in the tool in order to provide a complete, detailed dataset for any kind of network analysis.

Further classification of the customers is necessary to include more demographic and social characteristics for better representation of the population. This should also be associated with the type of the appliances that will equip the simulated households.

### **7.6.2 Future load replacement and DSM implementation**

The calculated magnitude of potential reductions suggests that DSM actions on non-critical loads applied at both the LV level and at a larger scale can lead to reductions in price and GHG emissions comparable to those achieved by DG. In the future, this analysis could be expanded to a larger section of the network to investigate this possibility. Furthermore, a network analysis could be performed to study the reaction of the network characteristics to these DSM actions and identify any further potential benefits.

### **7.6.3 Voltage control for demand reduction**

The proposed methodology should be extended to higher voltage level and include more LV networks in order to study the effect in greater scale, i.e. MV where OLTC transformers are present and the CVR method can be applied. Also, the compatibility of this methodology with any other existing control schemes should be investigated to develop an optimised control algorithm.

Another objective of further study should be the analysis of the effect on the potential benefit, in case that the future demand and the electrical characteristics differentiate significantly or the voltage levels vary from the current nominal values allowing for further voltage reduction.

### **7.6.4 Follow-up projects**

Some of the above future work is included in other projects that expand the research on DSM and smart grids in the Institute of Energy Systems in the University of Edinburgh. ADVANTAGE project, funded from the European Community's Seventh Framework Programme, is one of them. The objective of this project is to acquire a detailed understanding of both power engineering and communications issues that are involved in the design and implementation of the smart grid and its subsystems [135] and a part of it deals with the problem of optimal load clustering for demand-side management. The developed load modeling tool is one of the main tools that are being used by the ADVANTAGE researchers.



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## Appendix A

# Appliances library

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### A.1 Cold loads

**Table A.1:** Power ranges and ownership statistics for cold devices [1, 100, 103].

Load	Device ownership (%)		Power Demand		
	Primary	Secondary	On period (W)	Off period (W)	Distribution
Group 1	20.7	80	36-45	0	Normal: $\mu = 40, \sigma = 1.5$
Group 2	79.3	20	25-252		Normal: $\mu = 139, \sigma = 23$
Group 3	91.2		29-167		Normal: $\mu = 98, \sigma = 23$
Group 4	33		28-186		Normal: $\mu = 107, \sigma = 26$

### A.2 Wet loads

**Table A.2:** Ownership statistics and consumed energy of operation cycle of wet loads [1, 105].

Load	Ownership statistics (%)	Power demand kWh/cycle
Dishwasher	35	1.1-1.8
Washing machine	93	0.6-1.5
Tumble dryers	69	2.4-4.2
Washer dryers	18	3-5.5

## A.3 Consumer electronics

### A.3.1 Low-power and supplementary devices

**Table A.3:** Ownership statistics and rated power ranges for supplementary and low power appliances[24, 109, 112].

Appliance	Device ownership (%)	Power demand		
		In-use (W)	Stand-by (W)	Distribution
Set-top box	93%	5-18	5-11	Normal: $\mu = 12$ , $SD = 2.2$
Video player	88%	5-18	5-11	Normal: $\mu = 12$ , $SD = 2.2$
Audio appliances	90%	18-30	5-6	Normal: $\mu = 24$ , $SD = 2$
Game consoles	44%	13-197	2-4	Uniform

**Table A.4:** Statistics on game consoles ownership per type and power consumption [136].

Type	Device ownership (%)	Power demand	
		Mean Power (W)	Stand-by Power (W)
PlayStation 3	27.9	23-197	1-3
Xbox 360	29.5	67-185	2-3
Nintendo Wii	42.6	13-19	1-2

**Table A.5:** Statistics on game consoles ownership per type and power consumption [136].

### A.3.2 TVs

**Table A.6:** Statistics on TV ownership per technology and power range according to [103, 109].

Device	Device ownership (%)	Power demand		
		In use (W)	Stand-by (W)	Distribution
CRT	13.4	80-160	4-14	Normal: $\mu = 60$ , $SD = 13.3$
LCD/LED	71.0	80-300	1-3	Inverse Gaussian: $\mu = 60$ , $\lambda = 162$
PDP	15.1	60-130	2-4	Inverse Gaussian: $\mu = 186$ , $\lambda = 1241$
RP	0.5	145-340	2-4	-

## A.4 Information and Communication Technology

**Table A.7:** Ownership statistics and rated power ranges for ICT loads [1, 107, 110, 111].

Appliance	Device ownership (%)	Power demand		
		In-use (W)	Stand-by (W)	Distribution
Desktop	41	50-250	5	GEV: $k = 0.19$ , $\mu = 282$ and $\sigma = 95$
Laptops	78	20-120	5	GEV: $k = -0.15$ , $\mu = 58$ and $\sigma = 20$
CRT Monitors	2.1	60-85	2-5	Normal: $\mu = 72$ , $\sigma = 9$
LCD Monitors	39	10-140	2-5	Log-Logistic: $\mu = 3.3$ , $\alpha = 29$ , $\sigma = 0.2$
Printer/scanner	32.5	10-440	2-15	Inverse Gaussian: $\mu = 28$ , $\lambda = 148$
MFD	57	15-75	2-10	Inverse Gaussian: $\mu = 25$ , $\lambda = 130$
Routers	84	12-40	2-3	Normal: $\mu = 26$ , $\sigma = 4.7$
Phones	98	30-40	6-8	Normal: $\mu = 35$ , $\sigma = 1.7$

## A.5 Cooking

**Table A.8:** Cooking appliance ownership [1, 31, 101, 103, 112, 115, 116].

Device	Device ownership (%)	Power demand	
		Rated power (kW)	Distribution
Electric oven	62	2-3	Normal: $\mu = 2500$ , $\sigma = 155$
Electric hob	46	2-3	Normal: $\mu = 2500$ , $\sigma = 155$
Microwave Oven	92	0.6-1.15	Normal: $\mu = 862$ , $\sigma = 97$
Kettle	98	2-3	Normal: $\mu = 2500$ , $\sigma = 167$
Toaster	95	0.8-1	Normal: $\mu = 900$ , $\sigma = 33$
Food processor	95	0.15-0.33	Normal: $\mu = 240$ , $\sigma = 30$

## A.6 Miscellaneous loads

**Table A.9:** Power demand and ownership statistics for miscellaneous appliances.

Device	Device ownership (%)	Power demand	
		In-use power (kW)	Distribution
Vacuum cleaner	93.7	1.5-2.5	Normal: $\mu = 2$ , $\sigma = 0.2$
Iron	95	2-2.8	Normal: $\mu = 2.4$ , $\sigma = 0.1$
Hairdryer	95	1.8-2.2	Normal: $\mu = 2$ , $\sigma = 0.1$

## A.7 Lighting

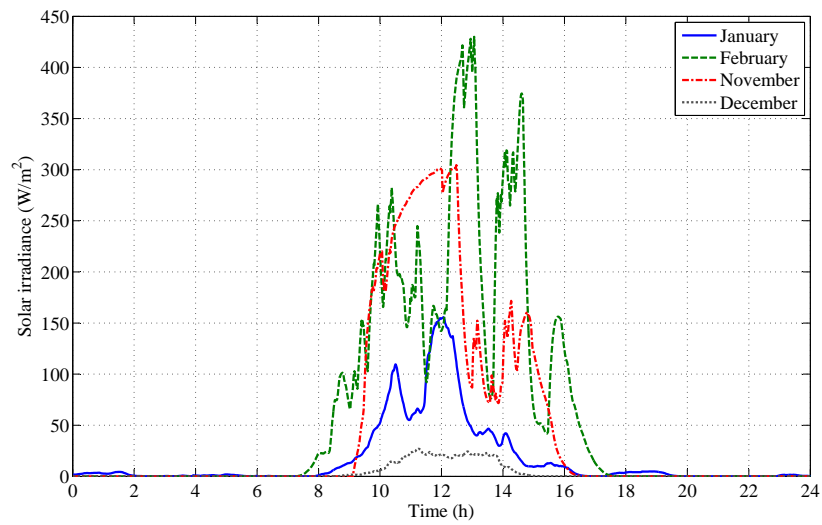
**Table A.10:** Percentage and power model of lamp types in stock [1, 50, 119, 120].

Type	Share (%)	Power Range (W)
GIL 40W	16.2	40
GIL 60W	16	60
GIL 100W	2.8	100
Halogen	27.4	5-500
LFL	2.7	80-150
CFL	34.3	8-23
LED	0.6	4-13

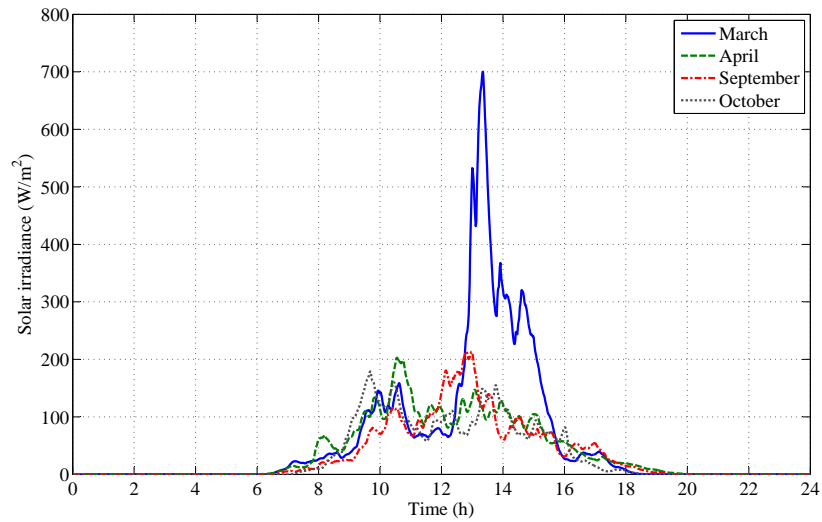


## Ambient conditions database

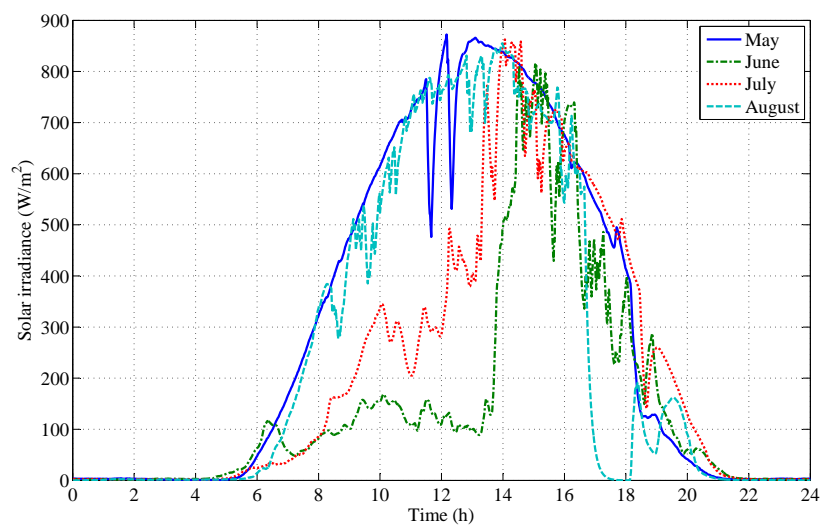
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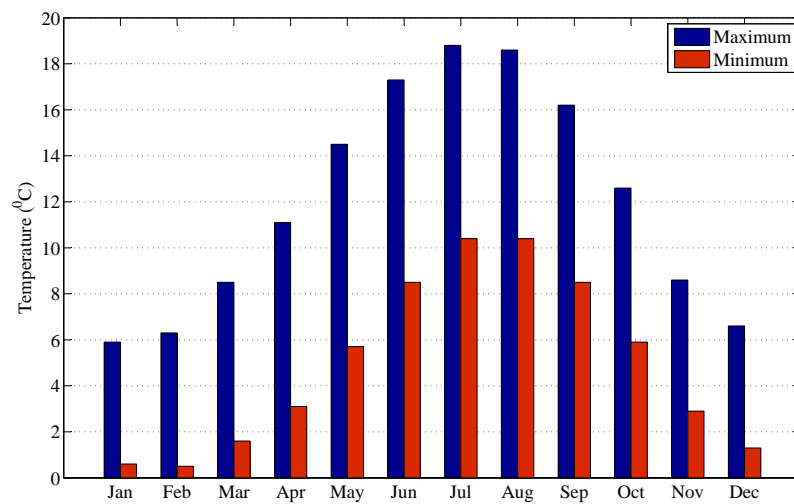
**Figure B.1:** Typical solar irradiance during winter in UK [98].



**Figure B.2:** Typical solar irradiance during spring and autumn in UK [98].



**Figure B.3:** Typical solar irradiance during summer in UK [98].



**Figure B.4:** Typical minimum and maximum external temperature in UK [99].

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## Appendix C

# List of publications

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The publications that were produced by the presented work are listed below:

1. A. J. Collin, G. Tsagarakis, A. Kiprakis, and S. McLaughlin, "Development of low-voltage load models for the residential load sector," *Power Systems, IEEE Transactions on*, vol. 29, no. 5, pp. 2180–2188, 2014.
2. G. Tsagarakis, R. C. Thomson, A. J. Collin, G. P. Harrison, A. E. Kiprakis, and S. McLaughlin, "Assessment of the cost and environmental impact of residential demand-side management," *Industry Applications, IEEE Transactions on*, in reviewing process, 2014.
3. G. Tsagarakis, A. Collin, and A. Kiprakis, "A statistical survey of the uk residential sector electrical loads," *International Journal of Emerging Electric Power Systems*, vol. 14, no. 5, pp. 509–523, 2013.
4. G. Tsagarakis, R. C. Thomson, A. Collin, G. P. Harrison, and A. Kiprakis, "Assessment of the cost and environmental impact of demand side management on residential sector," in *9th International Conference on Ecological Vehicles and Renewable Energies (EVER), 2014 IEEE*, Monte Carlo, Monaco. IEEE, Mar. 2014.
5. G. Tsagarakis, A. J. Collin, A. E. Kiprakis, and S. McLaughlin, "Voltage control of UK residential customers for power reduction," in *PowerTech 2013 IEEE Grenoble*. IEEE, Jun. 2013.
6. A. J. Collin, G. Tsagarakis, A. E. Kiprakis, and S. McLaughlin, "Multi-scale electrical load modelling for demand-side management," in *Innovative Smart Grid Technologies (ISGT Europe), 2012 3rd IEEE PES International Conference and Exhibition on*. IEEE, Oct. 2012.
7. G. Tsagarakis, A. J. Collin, and A. E. Kiprakis, "Modelling the electrical loads of UK residential energy users," in *Universities Power Engineering Conference (UPEC), 47th International*, London, IEEE, Sep. 2012.

A selection of the key publications that represent the research, i.e. 1, 4 and 5, follows for quick reference. Permission for their publication has been obtained by the participants.

# Development of Low-Voltage Load Models for the Residential Load Sector

Adam J. Collin, *Member, IEEE*, George Tsagarakis, *Graduate Student Member, IEEE*,  
Aristides E. Kiprakis, *Member, IEEE*, and Stephen McLaughlin, *Fellow, IEEE*

**Abstract**—A bottom-up modelling approach is presented that uses a Markov chain Monte Carlo (MCMC) method to develop demand profiles. The demand profiles are combined with the electrical characteristics of the appliance to create detailed time-varying models of residential loads suitable for the analysis of smart grid applications and low-voltage (LV) demand side management. The results obtained demonstrate significant temporal variations in the electrical characteristics of LV customers that are not captured by existing load profile or load model development approaches. The software developed within this work is made freely available for use by the community.

**Index Terms**—Load modelling, low-voltage network, markov processes, power demand, residential load sector.

## I. INTRODUCTION

THE influence of load characteristics on the operation and performance of electrical power systems is widely recognised. Accordingly, significant effort has been expended in developing load models for a range of power system studies, e.g. [1]–[3]. However, since the last major review of load models in 1995 [1], there have been many changes in the operation of the electrical power system and in the characteristics of loads, resulting in a need to update existing load models and produce new ones. This is reflected by a renewed interest in both industry and academia [4].

One of the main areas where this is particularly evident is in the modelling of the residential customers connected to the low-voltage (LV) distribution network. Traditionally, these networks and loads would have been represented by bulk aggregate load models for the analysis of medium and high voltage networks, e.g. [2], [5], [6], but there is a need for better representation of these networks, and the connected load, to support the growing number of research areas associated with the LV networks, e.g. demand-side management (DSM) and electric vehicle integration.

Recent research on the modelling of residential customers has focussed on representing the influence of user behaviour characteristics on energy use patterns, e.g. [7]–[11], and the physical components within the aggregate load, e.g. [12]–[15]. However, the correct representation of load in power

system studies requires both of these components: the load profile, which specifies how the power demand of the modelled load varies across the specified time, and the electrical load model, which specifies how the electrical characteristics of the load, i.e. how the power is drawn from the supply system, change with respect to time. Although the development of residential customer load profiles and models of the individual load components are relatively well represented in existing literature, there is still a lack of publicly available load models which bring these together.

In this paper, the two research streams are combined to present a methodology for developing LV load models of the residential load sector. As the user behaviour drives the electrical power demand, the modelling philosophy starts from the behaviour of individual users which are represented using a Markov chain Monte Carlo (MCMC) modelling approach. The user activity profiles are then converted into active and reactive power demand profiles and the corresponding load models by using a large database of load statistics and a library of detailed load models of the individual load components which have been developed in previous research [16]–[20]. The methodology is implemented using the UK residential load sector as an example, and the various stages of the modelling process are validated against available UK statistics.

The main contribution of this paper is the development of LV load models which are able to retain the stochastic variations which characterise the residential load sector. The load models are able to provide the expected temporal variations in the load profile but also provide more detailed information on the short-term and long-term variations of the electrical characteristics of the load than currently available load models of the residential load sector. Although any available load model form of the individual load components may be incorporated in the methodology, widely used static load model forms are used in this paper to illustrate and compare the temporal changes in load characteristics for three distinguishing system loading conditions: maximum, minimum and the year average demand. Including these variations will allow for a more accurate assessment of the performance of LV networks, which is also demonstrated in this paper.

The load modelling methodology is described in Section II and is illustrated in Section III by the UK residential load sector example, although the approach is more widely applicable. The developed load models are used to highlight differences in active and reactive power flows in Section IV. The conclusions are discussed in Section V. The developed software is made freely available for use by the community at [21].

The research is funded by the Research Councils UK Energy Programme under Grant EP/I000496/1.

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## II. LOAD MODEL DEVELOPMENT METHODOLOGY

In the residential load sector, power demand is driven by user behaviour. The advent of "smartly driven" appliances may alter the time of use of certain loads, the habitual patterns of the user will still drive the main periods of activity within the dwelling. For that reason, the modelling philosophy in this paper starts from consideration of the user activities.

The power demand is intrinsically connected to a large number of factors which are typically used when defining user groups for modelling purposes, including: the characteristics of the user [7], [9], the number of household (HH) occupants [8], [11], the building type [9] and the time of year [9]. In the research presented here, each household is defined by the number of occupants  $m$  in the household, which is hereafter referred to as the household size, and the user type of each occupant. Each household occupant is labelled as 'working' or 'not working', with children classified as 'working' occupants. Therefore, there are  $m+1$  possible occupant combinations for each household size, e.g. household size one can have zero or one working occupant. More detailed user groups may be formed in future, e.g. based on the age of occupants, if required to analyse specific network scenarios.

The modelling approach developed in this paper is divided into three stages:

- 1) user activity modelling;
- 2) conversion of user activities to electrical appliance use;
- 3) aggregation of the electrical appliances to build household power demand profiles and load models.

These stages are presented in Fig. 1, which displays the information flows in the modelling framework. The input variables are configured by user defined parameters which determine the aggregate size, the aggregate composition, the day of the week and the month of the year. The simulation time step for user activity modelling is 10min, due to the available input data, and is reduced to 1min during the conversion to power demand to more accurately capture the short term variations in load use.

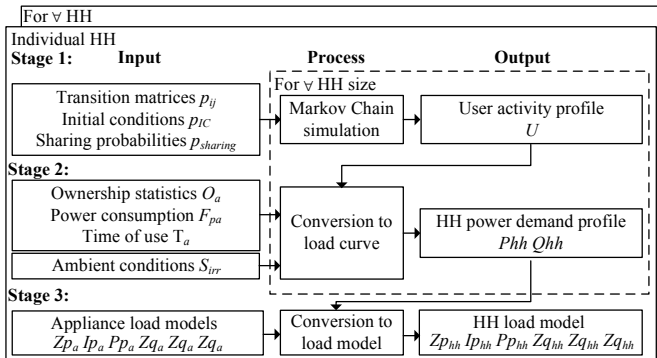


Fig. 1: Load model development work flow.

### A. User activity input data

The most prominent publically available data for user activity information is in Time Use Surveys (TUS). The UK TUS (available from [22]) was used as the main source of input data for modelling the user activities in this study. Similar studies are available for a large number of countries around the world (an exhaustive TUS bibliography is available in [23]), to which the method described in this paper can be applied.

### B. User activity modelling

To simplify the analysis, 13 user activity states are defined. The activity states include the main user activities which may result in electrical appliance use and also acknowledges the building occupancy, which is vital for the modelling of lighting and heating loads. As electrical appliances may be shared within multiple occupancy households, this functionality is also included in the relevant activity states. Table I contains further information on the defined user activity states.

Due to the high variability, probabilistic approaches are normally applied to model user behaviour. For example: [7] utilises probabilistic functions, while a Markov chain (MC) approach is implemented in [10] and [8] combines the two approaches. A thorough review of user behaviour modelling research is available in [24]. A combined MCMC approach is used to synthesis the user activity profiles  $U$  in this paper.

TABLE I: User activity state definitions.

id.	User activity state Definition	Electrical Use	Appliance Sharing
1	Non-electrical activity in home	N	n/a
2	Sleeping	N	n/a
3	Wash/dress	Y/N	N
4	Food preparation	Y/N	N
5	Dishwashing	Y/N	N
6	Cleaning house	Y/N	N
7	Laundry	Y/N	N
8	Ironing	Y	N
9	Computing	Y	Y/N
10	Watching TV	Y	Y/N
11	Watching video/DVD	Y	Y/N
12	Listening to music/radio	Y	Y/N
13	Out of house	N	n/a

where: Y - yes, N - no, n/a - not applicable

The MC transition probabilities  $p_{ij}$  are calculated by checking all transitions  $n_i$  from state  $i$  between time  $t$  and  $t+1$  and the total number of transitions  $n_{ij}$  between state  $i$  and state  $j$  between time  $t$  and  $t+1$ . The transition probability calculation is given by (1). In total, there are 143 transition matrices each containing  $13 \times 13$  elements (for each household size and user type), i.e. one matrix for each time step transition. The user activity state at  $t(1)$  is used to define the probability distribution of initial conditions  $p_{IC}$ .

$$p_{ij}(t) = \frac{\sum_{j=1}^J n_{ij}}{n_i(t)} \quad \forall i, t \quad (1)$$

where:  $p_{ij}(t)$  is the transition probability from state  $i$  to state  $j$  (which can include  $i=j$ ) between time  $t$  and  $t+1$ ,  $n_{ij}(t)$  is the number of transitions from state  $i$  to state  $j$  between  $t$  and  $t+1$ ,  $n_i(t)$  is the total number of transitions from state  $i$  between  $t$  and  $t+1$  and  $J$  is the total number of activity states.

For multiple occupancy households, there is a probability that certain appliances will be used by more than one occupant at any given time. To calculate the device sharing probability, empirical data from the UK TUS "with" variable is analysed to develop a probabilistic function. This variable has the following states: alone, with another person (household member) and with another person (not household member). This is a suitable indicator for device sharing, as all electrical appliances which can be shared will utilise at least one of the user's senses and are not expected to be used within the same room at the same

time. Therefore, if two or more users have the same activity state and "with" variables at the same time step, it is assumed that the electrical appliance is shared.

The device sharing probability  $p_{sharing}$  is determined by comparing all household users activity state and "with" variables at every time step. The  $p_{sharing}$  is calculated by the ratio of users having the same activity and "with" variable  $S_{sharing}$  to the users who have only the same activity  $S_{same}$  (2).

$$p_{nm,sharing}(i,t) = \frac{S_{nm,sharing}(i,t)}{S_{nm,same}(i,t)} \quad \forall i, n, m, t \quad (2)$$

where: counter  $S_{nm,same}(i,t)$  represents the number of occurrences of activity  $i$  at time  $t$  for  $n$  household members of household size  $m$ ,  $S_{nm,sharing}(i,t)$  is the number of occurrences of activity  $i$  at time  $t$  which have the same "with" variable and  $p_{nm,sharing}(i,t)$  is sharing probability of  $n$  members of household size  $m$  sharing activity  $i$  at time  $t$ .

This functionality is included in the modelling approach by including an additional stage after the user activity time series' have been synthesised. An algorithm identifies every time period when multiple users have the same activity and compares the  $p_{sharing}$  against a randomly generated uniform number  $r$ . This is illustrated in Fig. 2 for a two person household. The activity state of the secondary user  $U_2$  is set to 1 if the electrical device is shared, thus maintaining the correct household occupancy characteristics:

$$U_2(i,t) = \begin{cases} 1 & r \leq p_{nm,sharing}(i,t) \\ i & r > p_{nm,sharing}(i,t) \end{cases} \quad (3)$$

where:  $p_{nm,sharing}(i,t)$  is the predetermined sharing probability for activity  $i$  at time  $t$  and  $r$  is the random number.

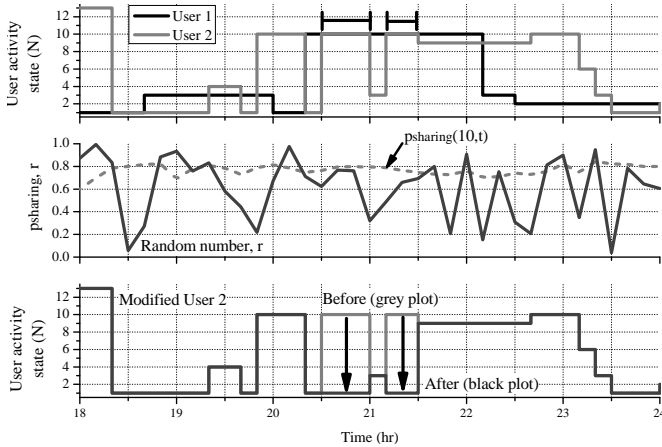


Fig. 2: Device sharing implementation example for a two person household with two working occupants.

### C. Conversion to electrical power demand

In the next stage of the modelling process, the synthesized user activity times series' are converted into electrical loads using a database containing device ownership, usage, operating power range and standby power statistics [20]. The database also includes representation of the different operating phases of appliances, e.g. change in power demand during washing machine operating cycle, which are maintained within the developed time varying load models (with full details available in [20]). These data are supplemented with the typical

displacement power factor value and the electrical load model, which are presented in Table II in the following section.

The majority of the user activity states defined in Table I have a direct conversion to an electrical appliance  $a$ . For such activities, only the device ownership  $O_a$  and statistical distributions of operating power are required to convert the activity to electrical power demand. However, for the activities which may or may not require an electrical appliance, additional time of use statistics are required. The user activity state  $U_i$  at time  $t$  is combined with  $O_a$  and probabilistic functions  $T_{i,a}$  of use of electrical appliance  $a$  associated with user activity  $i$  to convert to a power demand profile for appliance  $P_a$  (4).

$$P_a(t) = (U_i(t) \cap O_a \cap T_{i,a}(t)) X \quad \forall a \quad (4)$$

where:  $X$  is a random value for power of appliance  $a$  (in watts), with a probability distribution  $f_{P_a}(x)$  as described in [20].

The device use duration is selected from typical appliance usage profiles and requires the simulation time step to be converted to 1 min. This allows for the correct representation of loads with use duration less than 10 min and is implemented by randomly allocating the device start time within the 10 min period. For certain appliances, the  $T_{i,a}$  is updated after use to ensure that appliance usage maintains the expected consumption characteristics. The total household demand is obtained by summing the demand of all household appliances:

$$P_{hh}(t) = \sum_{a=1}^A P_a(t) \quad \forall t \quad (5)$$

$$Q_{1,hh}(t) = \sum_{a=1}^A P_a(t) \tan(\cos^{-1}(PF_{1,a})) \quad \forall t \quad (6)$$

where:  $P_{hh}$  and  $Q_{1,hh}$  are the household active and (fundamental) reactive power demand,  $P_a$  and  $PF_{1,a}$  is the active power demand and displacement power factor of appliance  $a$  and  $A$  is the total number of appliances.

Certain loads in the residential load sector should be modelled using "physical" models, i.e. using environmental variables as input parameters [15]. In the UK, the penetration of electric heating, ventilation and air-conditioning (HVAC) systems is relatively low (around 7 % [25]) so the main seasonal variations are a result of the lighting load, i.e. in response to seasonal changes in solar irradiance  $S_{irr}$ . The physically based lighting model developed in [26] has been implemented in the MATLAB environment and integrated with the code developed in this paper. The software can be extended in future work to include HVAC systems.

### D. Electrical load model

For power system analysis, the developed load profiles must be converted into a recognised load model form. Although any model form can be used within the load modelling methodology, only the active and reactive power demand characteristics, as represented by the widely used exponential (7) and polynomial/ZIP (8) load model forms, are used to illustrate the temporal variations in load characteristics of the models developed in this paper. All models are developed in ZIP form (as they better represent modern non-linear loads), but the characteristics are then converted to the exponential model

form using (9) [4] for a clearer description of the electrical characteristics.

$$P = P_0 \left( \frac{V}{V_0} \right)^{n_p} \quad (7)$$

$$P = P_0 \left[ Z_p \left( \frac{V}{V_0} \right)^2 + I_p \left( \frac{V}{V_0} \right) + P_p \right] \quad (8)$$

$$n_p \approx \frac{2 \times Z_p + 1 \times I_p + 0 \times P_p}{Z_p + I_p + P_p} \quad (9)$$

where:  $P$  is the active power demand at supply voltage  $V$ ,  $P_0$  is the rated active power demand at nominal supply voltage  $V_0$ ,  $n_p$  is the exponential model active power coefficient and  $Z_p$ ,  $I_p$  and  $P_p$  are the constant impedance, constant current and constant power coefficients of the polynomial model. Similar expressions exist for reactive power.

To develop the household load model, a component-based load modelling approach is implemented within the methodology. This simplifies the modelling process by reducing the large number of loads in the residential sector to only a few load components by grouping loads with similar characteristics. As outlined in [16], the residential loads are grouped into the following components:

- 1) Power electronics: mainly consumer electronics (CE) and ICT loads. Variations exist depending on the power factor correction (PFC) circuit included within the switch-mode power supply (SMPS)
- 2) Resistive loads: heating elements
- 3) Lighting: including general incandescent lamps (GIL) and compact fluorescent lamps (CFLs)
- 4) Directly connected motors: used in white appliances and water pumps. Variations exist based on the motor loading characteristics and inclusion of a start/run capacitor
- 5) Drive controlled motors: often used in HVAC systems.

The models of the individual load components are given in Table II, with further details provided in [16], [19].

TABLE II: Polynomial load model coefficients [16], [19].

Load	PF <sub>1</sub>	Polynomial Model					
		$Z_p$	$I_p$	$P_p$	$Z_q$	$I_q$	$P_q$
GIL	1	0.43	0.69	-0.12	-	-	-
CFL	0.91	-0.01	0.96	0.05	0.1	-0.73	-0.37
RSIR <sub>QT</sub>	0.62	0.10	0.10	0.80	1.40	-0.91	0.50
CSCR <sub>CT</sub>	0.9	0.50	-0.62	1.11	1.54	-1.43	0.89
Resistive	1	1	0	0	-	-	-
SMPS <sub>noPFC</sub>	0.99	0	0	1	-3.63	9.88	-7.25
SMPS <sub>pPFC</sub>	0.97	0	0	1	0.45	-1.44	1.99
SMPS <sub>aPFC</sub>	1	0	0	1	-	-	-

where: SMPS<sub>noPFC/pPFC/aPFC</sub> are SMPS with no-PFC, passive-PFC and active-PFC, RSIR is resistive start-inductor run motor, CSCR is capacitor start-capacitor run motor, subscripts QT/CT are quadratic/constant torque motor loading conditions and PF<sub>1</sub> is displacement power factor.

From the data in Table II, the active power coefficients of lighting loads are predominantly constant current load types, while motor loads and power electronics load are approximately constant power load types. The reactive power coefficients of the main reactive load (induction motors) tend towards constant impedance, while capacitive CFLs are constant current. However, it is the combination of these loads which will determine the overall electrical characteristics of

the household. At any time instance the load models of the individual components are aggregated to produce a load model for the entire household using a weighted summation, given by (10) and (11) respectively:

$$\begin{bmatrix} Z_{p_{hh}} \\ I_{p_{hh}} \\ P_{p_{hh}} \end{bmatrix} = \sum_{a=1}^A \frac{P_a}{P_{hh}} \begin{bmatrix} Z_{p_a} \\ I_{p_a} \\ P_{p_a} \end{bmatrix} \quad (10)$$

$$\begin{bmatrix} Z_{q_{hh}} \\ I_{q_{hh}} \\ P_{q_{hh}} \end{bmatrix} = \sum_{a=1}^A \tan(\cos^{-1}(PF_{1_a})) \frac{P_a}{P_{hh}} \begin{bmatrix} Z_{q_a} \\ I_{q_a} \\ P_{q_a} \end{bmatrix} \quad (11)$$

where:  $Z_{p_{hh}}$ ,  $I_{p_{hh}}$ ,  $P_{p_{hh}}$ ,  $Z_{q_{hh}}$ ,  $I_{q_{hh}}$  and  $P_{q_{hh}}$  are the real and reactive components of the aggregate household ZIP model,  $A$  is the total number of household appliances,  $a$  is the appliance index,  $P_a$  is the power demand of appliance  $a$ ,  $P_{hh}$  is the total household power demand,  $Z_{p_a}$ ,  $I_{p_a}$ ,  $P_{p_a}$ ,  $Z_{q_a}$ ,  $I_{q_a}$ ,  $P_{q_a}$  and  $PF_{1_a}$  are the real and reactive ZIP model components and displacement power factor of appliance  $a$ .

### E. Network simulation

The load profiles and load models of the individual load models can be directly implemented for analysis of LV networks. Demographic statistics, e.g. [27], should be used to select the correct proportion of different household size and user types within the aggregate.

## III. UK RESIDENTIAL LOAD SECTOR

In this section, the proposed load modelling methodology is applied to the UK residential load sector in order to validate the functionality of the model and to highlight the temporal variations in the load model characteristics. Although the modelling approach is able to reproduce the stochastic variations which characterise individual households, the functionality of the model developed in this paper is verified by checking the consumption characteristics against UK data, which are only available for a UK wide aggregation. Therefore, a sample size of 10,000 individual household was selected and the aggregate composition input to the model was configured to represent the overall UK statistics, which are shown in Table III.

TABLE III: UK population statistics as percentage [27].

HH size	Working occupants				
	0	1	2	3	4
1	12	23	-	-	-
2	3	8	23	-	-
3	1	4	11	1	-
4	1	3	8	1	1

### A. User activity modelling

The UK TUS data was processed to obtain a representative set of input data of user activity states for every household size and user type combination. Although not considered in detail in this paper, the weekday and weekend data was separated to create distinct user behavioural models for each case. The largest household size considered in the analysis is four occupants, resulting in a total of 14 different household size and user combinations. This covers 95 % of the UK population [27] and is suitable for representing the overall characteristics of the total population.

The UK TUS data was used to calculate the initial condition probabilities, MC transition matrices and device sharing probabilities, which are implemented in MATLAB. The transition path is determined by comparing a random number generated from a set of random numbers,  $U \in [0, 1]$ , against the transition probabilities given by (1) for each time step. The output is a times-series of user activities with 10min resolution.

A correlation coefficient  $\rho$  (12) is used to assess the accuracy of the developed model by comparing the simulated activity time series with original TUS data for all household sizes. One example is presented in Fig. 3a), where it is shown that the MCMC user activity model is able to accurately replicate the behavioural characteristics for the cooking activity. The correlation coefficient value is greater than 0.99 for all user types and activity states, confirming the accuracy of the developed MCMC user activity model.

$$\rho_{XY} = \frac{\sigma_{XY}}{\sigma_X \sigma_Y} = \frac{\sum_{i=1}^{13} \sum_{t=1}^{144} (X_{i,t} - \bar{X})(Y_{i,t} - \bar{Y})}{\sqrt{(\sum_{i=1}^{13} \sum_{t=1}^{144} (X_{i,t} - \bar{X})^2)(\sum_{i=1}^{13} \sum_{t=1}^{144} (Y_{i,t} - \bar{Y})^2)}} \quad (12)$$

where:  $X$  and  $Y$  are the simulated and TUS data,  $\sigma_X$  and  $\sigma_Y$  are the variance of  $X$  and  $Y$ ,  $\sigma_{XY}$  is the covariance between  $X$  and  $Y$ ,  $i$  and  $t$  are the activity and time index and  $\bar{X}$  and  $\bar{Y}$  are the mean value of  $X$  and  $Y$ .

### B. Conversion to electrical appliance use

Fig. 3 illustrates the conversion of the 'cooking' activity state to electrical power demand for the aggregate group of customers. The discrete probability functions of appliance use  $A_{ij}$  are shown below the user behaviour. For kettles and microwaves, the power demand is assumed constant during operation and selected from a uniform distribution (intervals are defined as: kettle [2, 3] kW and microwave [0.6, 1.2] kW, with device duration selected from a uniform distribution between [2, 5] mins. For electric ovens, the power demand will vary based on the device duty cycle  $D = 0.5$  (5 min cycle) within typical power ranges [0, 2] kW, with device duration selected from a uniform distribution between [30, 90] mins. The fitting values for the cooking consumption are  $\sigma_{XY} = 0.96$  and  $RMSE = 0.08$ , which indicates that the developed model is able to reproduce the expected demand.

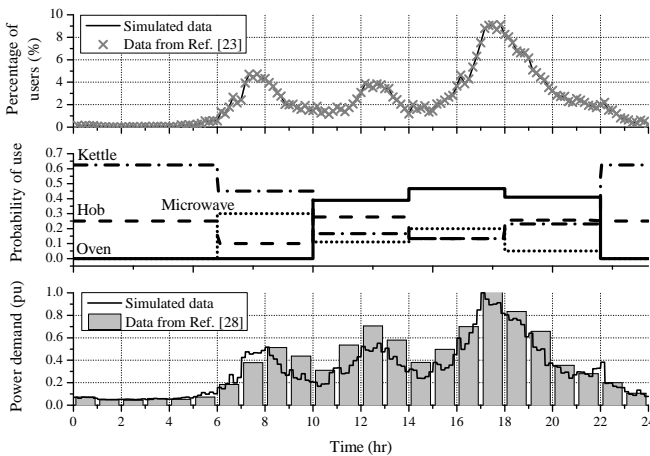


Fig. 3: Conversion of cooking user activity to power demand.

### C. Conversion to electrical power demand

To thoroughly assess this stage in the load model development process, the two prominent load features are verified: the load profile shape and the contribution of each load to the consumption. Fig. 4 compares the normalised aggregate output for 10,000 household simulated profiles against the normalised typical UK residential demand profile presented in [29] for weekday winter loading conditions. This also includes the simulated load profiles of the months which comprise winter (Oct. - Feb. [29]). A comparison of the two curves confirms the accuracy of the model, with a difference in daily consumption of 2.2 %,  $RMSE = 0.05$  and  $\sigma_{XY} = 0.98$ . The developed model has the same temporal characteristics with the measured data as the morning and evening peaks, and night and mid-day plateaux, coincide in time and magnitude.

Further validation of the model is achieved by calculating the daily energy consumption of the individual loads within the simulated aggregate and comparing with UK wide statistics in [25]. These results are presented for the average household daily energy consumption in Fig. 5. The maximum absolute percentage error is less than 5%, which further confirms the ability of the presented modelling approach to represent the characteristics of the residential load sector.

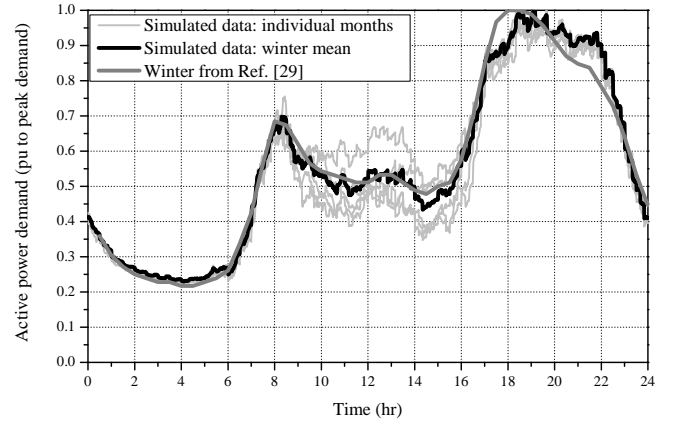


Fig. 4: Comparison between load curve from the developed model and data in [29] for maximum loading conditions.

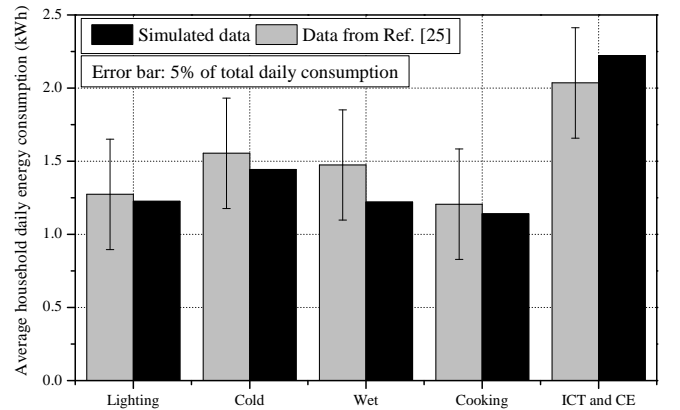


Fig. 5: Comparison between proposed model and data in [25] for load contribution to daily UK residential energy consumption.



#### D. Electrical load model

The load profiles in Fig. 4, do not contain information on the electrical characteristics of the load. The corresponding load model values are obtained using the load profile data of the individual households and the load model aggregation procedure (10) and (11) to create a separate ZIP model for each of the 10,000 households. The developed ZIP models are converted to the exponential model form for a clearer description of the electrical characteristics. Fig. 6 displays the mean and standard deviation values of all simulated households for the three considered loading conditions, showing the evolution of the active  $n_p$  and reactive  $n_q$  power parameters.

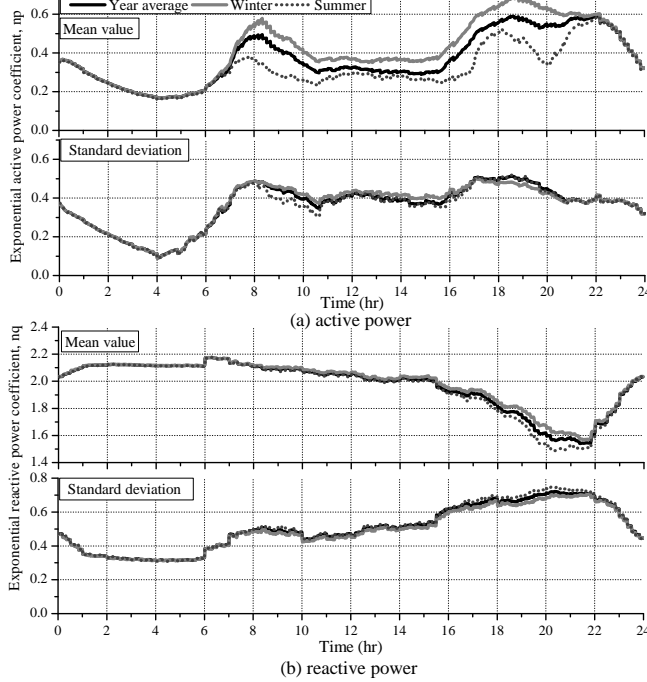


Fig. 6: Comparison between load model coefficients for characteristic loading conditions.

Due to the physical significance of the load model, there is a clear correlation between the mean value of the parameter  $n_p$  and the active power demand profile. The value of  $n_p$  is lowest during the night and tends towards constant real power characteristics. This is because most loads are off, except the cold loads which have approximately constant real power characteristics (see Table II). The higher  $n_p$  values coincide with the peaks in the power demand profile and lie between constant power and constant current load types. This is a result of the aggregate effect of the large number of, relatively, lower power lighting (constant current) and power electronics loads (constant power) with a smaller number of higher rated power resistive loads. Comparing the winter, summer and year average values, the effect of increased lighting load is clearly visible and is manifested by the increased value of  $n_p$ .

There is very little difference in the standard deviation of the load model parameter for different loading conditions. The standard deviation will increase slightly during periods of high demand, as a result of more loads being used. However, this effect is less pronounced than in the mean value, as a result of load aggregation. The value of standard deviation is, generally, comparable to the mean value of the load model coefficient

which highlights the large variation between households.

For the majority of the 24-hour period, the coefficient  $n_q$  is dominated by motor loads, and will tend towards constant impedance load type. However, as more loads are used within the household, the value of  $n_q$  will reduce as the contribution from other loads with lower exponent values increases. The seasonal difference is negligible, but it is possible that this characteristic will change as capacitive CFLs replace GILs.

The contribution of the research presented in this paper is highlighted by comparing with existing residential load models, such as those presented in Table IV. Although these models are a valuable resource, they were developed from measurements at the MV level, which are not widely available. However, as demonstrated, the models presented in this paper can be obtained using only publicly available datasets.

As previous research has focussed on the MV level, the models include the influence of MV/LV network components. While this will provide accurate MV load models, they are not suitable for analysis of LV networks. The values of the developed load models are generally lower than the values of the existing models. This can be attributed to the aggregation process inherent in the MV models, which will smooth out variations between individual households, and the effect of the network, especially distribution transformers.

TABLE IV: Existing residential load sector models.

Ref	Year	V (kV)	Loc.	Time	Parameters
[2]	1993	ns	US	S	$n_p=0.9-1.4, n_q=2.4-2.9$
				W	$n_p=1.5-1.7, n_q=2.5-3.1$
[5]	2004	21	US	ns	$n_p=0.68, n_q=1.91$
				S	$n_p=1.162, n_q=4.016$
[6]	2008	10	Serbia	W	$n_p=1.401, n_q=3.460$
				Y	$n_p=1.245, n_q=3.899$

where: S- summer, W- winter, Y-year and ns- not stated.

Note: the ZIP model presented in [5] has been converted to form (7)

#### IV. NETWORK ANALYSIS

##### A. UK low voltage network

A generic UK LV network is modelled as supplied by a single 500 kVA, 11/0.4 kV step-down transformer supplying 384 residential customers through four feeders. The network is balanced with 32 customers per phase per feeder. Each feeder consists of 300m three-phase cable, with customers evenly distributed along its length, i.e. at 94m intervals, and connected by 30m of single-phase service cable to the three-phase supply. Further details of the network are available in [30].

##### B. Simulation approach

In the UK, the LV network operates with a nominal voltage of 230/400 V with a tolerance range of +10% / -6%. As the actual voltage magnitude will vary based on the conditions of the LV network and the external network, the external network is configured to give three characteristic voltage conditions:

- $V_{nom}$  - transformer primary winding voltage at 1.0 pu;
- $V_{min}$  - last residential customer is not lower than 0.94 pu;
- $V_{max}$  - transformer primary winding voltage set to 1.1 pu.

These scenarios are included in the network simulation by setting the initial voltage on the 11 kV side of the 11/0.4 kV transformer to 1.0pu and 1.1pu for the nominal and maximum voltage conditions; for the minimum voltage condition, the initial voltage is set to ensure that the minimum voltage of

the last customer is not lower than 0.94pu for the time of peak demand. From the initial values, the voltage profile will change in response to the demand of the connected load.

For each voltage setting, loads representing the winter residential loading conditions (January weekday) are connected. The loads have been randomly synthesized using the methodology described in previous sections so as to be statistically representative of the UK average. The network results obtained using the load models developed in this paper are compared against those using constant (voltage independent) PQ load, which is still the most widely used static load model [4], and the constant  $I_pZ_q$  load model, which is a common assumption when modelling the residential load sector if more detailed load information is not available. Both constant load models are implemented with a power factor of 0.95 (inductive).

### C. Network analysis results and discussion

As the supply voltage magnitude changes, the power demand of the constant PQ loads will not change. There will be some change in the power as seen from the bulk supply point as a result of changing losses within the network, but the effect of this is small compared to the total load demand. However, the power demand of the detailed load models will change. As a general rule, the power demand will increase with an increase in supply voltage magnitude and vice-versa. This is illustrated for maximum voltage conditions in Fig. 7.

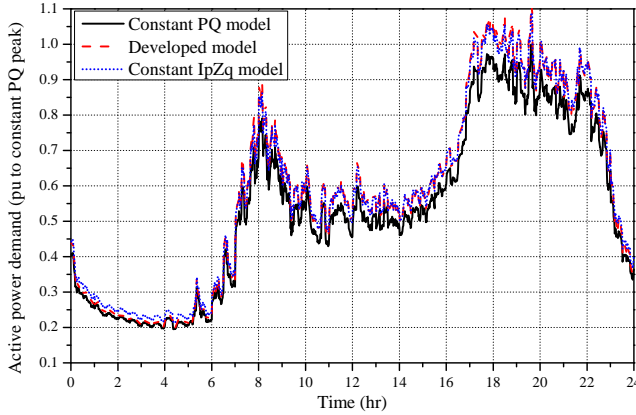


Fig. 7: Aggregate power demand for detailed model and constant PQ model for maximum voltage conditions.

In Fig. 7, the profile of the power supplied to the LV network is very similar to the profile of the  $I_pZ_q$  model. This is a further validation of the electrical characteristics of the developed load model. It is shown that even for this small network, the difference in calculated daily energy and instantaneous peak power is quite significant when using the voltage dependent load models, compared to the PQ model. At peak demand, the difference between the detailed model and the constant PQ and  $I_pZ_q$  models is around 10% and 2%, respectively. The largest difference is observed during the morning peak, where the difference between the detailed model and the constant PQ and  $I_pZ_q$  models is 12% and 3%. This also confirms that PQ models are inadequate for analysis of LV networks.

This is further demonstrated by the mean value results of multiple simulations summarised in Fig. 8. These values are calculated using the constant PQ load as the reference, therefore a negative value indicates that the values are lower

than the those of the constant PQ load. Although there is no significant difference in the calculated mean and peak active power between the voltage dependent models, the power factor of the developed model is varying widely; for all voltage settings it reaches a peak value close to 0.98 (lag) due to the capacitive lighting and the electronic loads dominant during the evening hours, and has a mean value that ranges from 0.9 (lag) for  $V_{\max}$  to 0.92 (lag) for  $V_{\min}$ , as an effect of the inductive base load.

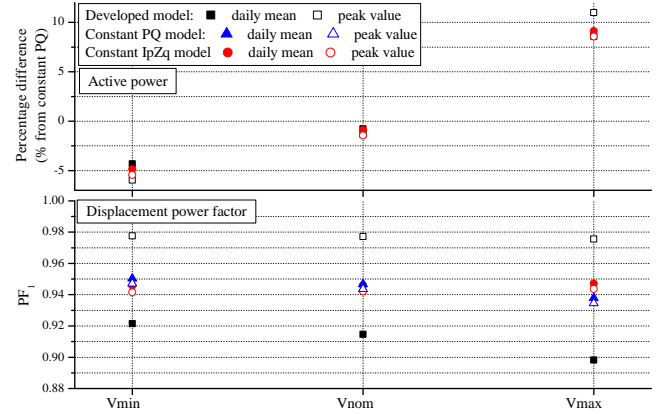


Fig. 8: Comparison between the calculated active power (top) and displacement power factor (bottom) for the simulated network using the developed, the PQ and the  $I_pZ_q$  models.

### V. CONCLUSION

In order to support the growing interest in LV networks, increased levels of modelling detail for all components within the system are required. The work presented in this paper contributes to the research area by presenting a load modelling methodology which is able to reproduce both the load profile and the detailed electrical characteristics of LV residential customers. As such, the modelling approach is able to represent the changes in the load characteristics due to system or user behaviour modifications. These characteristics make it particularly applicable to DSM and smart grid studies.

The methodology is illustrated by a case study of the UK residential sector using UK TUS data to demonstrate the effects of supply voltage magnitude on power demand. It should be noted, however, that the model is generic and can be developed using appropriate TUS data [23] to generate synthesized demand profiles and load models with any specific statistical and qualitative characteristics. The UK case study highlighted the temporal distribution of load parameters, which were displayed using simple static load models widely used in both static and dynamic power system analysis [4]. The presented load parameters are able to capture the short term variations in load characteristics which are hard to determine using traditional load modelling techniques.

As the approach is divided into discrete stages, this allows for the modification of user behaviour (e.g. deferral of appliances for peak-shaving) and addition (e.g. electric vehicles) or substitution (e.g. LED in place of incandescent and CFL lighting) of loads to be easily integrated within the modelling framework. Furthermore, the load model can be replaced by the more detailed circuit based form to assess network power quality in response to the previously mentioned changes. This

flexibility can be exploited in future research to investigate the impact of specific DSM scenarios on the operation and performance of wide-scale electrical power systems.

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# Assessment of the Cost and Environmental Impact of Residential Demand-side Management

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**Abstract**—The paper presents a detailed study of the potential impact on the cost and greenhouse gas emissions (GHG) through low voltage (LV) residential demand-side management (DSM). The proposed optimisation algorithm is used to shift non-critical residential loads, with the wet load category used as a case study, in order to minimise the total daily cost and emissions of GHG due to generation. This study shows that it is possible to reshape the total power demand and reduce the cost and emissions of demand to some extent. It is also shown that further optimisation of the cost leads to an increase in GHG emissions because of their conflicting nature.

**Keywords**—Demand Side Management, optimisation algorithm, load modelling, residential load, low voltage.

## I. INTRODUCTION

Customers' interest in the reduction of the cost of the daily power demand has increased. This cost does not only describe the price of electricity, but also the environmental cost, defined in this paper by generation greenhouse gas emissions (GHG). One method of altering the cost to the consumer is load manipulation through the actions of demand side management (DSM), which will impact on multiple aspects of the supply of electrical energy.

There have been several studies on DSM strategies, and their impact on energy demand, that are not directly connected to pricing or environmental causes, e.g. [1], [2], [3], [4], [5]. In the majority of these studies, the analysis is performed at higher voltage levels and loads are treated as aggregate amounts of energy, rather than as discrete appliances with operation cycles. However, this approach is not appropriate for the analysis of low-voltage (LV) networks, where many proposed DSM actions will be implemented.

At the LV level, the domestic energy demand depends on the mixture of the individual electrical appliances,

the behaviour of the residential users and environmental aspects (e.g. external temperature). It is the combination of these three factors which results in the stochastic nature of LV power demand and requires more detailed simulation techniques than those typically applied at the higher voltage levels. This generally requires consideration of the specific loads available for DSM, as load management must not impact on users' quality of life. The available loads, termed as 'non-critical', may be rescheduled without affecting the users. This is demonstrated in several studies that focus on specific load categories and examine how their manipulation could reduce the cost or the GHG emissions, e.g. electric vehicles (EV) and heat pumps [6], [7]. However, the analysis methods for EVs and heat pumps allow for interruption of their operation. As this is not true for most domestic appliances, the techniques are not directly transferable.

In this paper, an approach for DSM implementation on the LV residential load is presented, which includes consideration of device operation cycles. This employs a multi-objective optimisation algorithm in order to achieve the least economic and environmental cost of required daily energy with the minimum effort. The effort is defined as the percentage of the load that is required to be managed [8]. In order to calculate this, detailed residential load models are used to identify the use of 'non-critical' loads. The load models are then combined with typical profiles of cost and GHG emissions in the UK to reform the power demand.

The paper is structured as follows: in the first Section an overview of the proposed methodology is presented, followed by the problem formulation in Section II; Section III describes the properties of the optimisation algorithm; in Section IV, the case study is described and the results of the application of the methodology are presented and discussed; conclusions and suggestions for further work are given in Section V.

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## II. PROBLEM FORMULATION

In practice, LV residential load consists of the various appliances that exist in households and can be divided into two categories according to their necessity: critical and non-critical loads. Although the use of critical loads cannot be modified without changing the behaviour of household occupants, non-critical loads can be deferred so as to achieve the desired targets. An example of non-critical load category is wet loads, such as dishwashers, washing machines, tumble dryers and washing dryers. The operation of these loads can be postponed for some other time during the day if needed without noticeable obstruction to the users. Wet loads are responsible for a large percentage of the total daily power consumption (approximately 15%) for the UK [9]. The management of such loads can have significant impact on the total power demand, the cost of it to the customers and the total daily GHG emissions.

The calculation of active power demand before and after the load shifting requires the development of detailed power profiles of individual households to increase the accuracy of the results. In this paper, a previously developed combined Markov chain Monte Carlo model is implemented to simulate the UK residential demand, further details are available in [10]. The detailed profiles allow for realistic representation of the use of all residential appliances, including the wet loads, by the UK population.

## III. METHODOLOGY

The proposed methodology consists of a multi-objective optimisation algorithm for shifting the wet load category during the day. The objectives of the study are to simultaneously minimise the total daily cost of the power demand to the end user and the amount of GHG emissions that derive from supplying the power demand. In order to achieve these targets, the electricity price and GHG emissions profiles are combined in the optimisation algorithm and used as the drivers of the DSM actions on wet loads. A significant parameter is the estimation of the minimum number of shifted loads that are required for the best result.

### A. Optimisation problem definition

The objective functions of the proposed algorithm can be described mathematically by the Eq. (1-2).

$$\min\left(\sum_{i=1}^t c_{comb} = \sum_{i=1}^t x * c_{wi} + y * em_{wi}\right) \quad (1)$$

$$\min(n_{swl}) \quad (2)$$

where  $t$  defines the time steps, which in this study is equal to 1440 minutes,  $c_{comb}$  is the combined cost and is calculated by  $c_{wi}$  and  $em_{wi}$  which are the weighted values of the price and GHG emissions respectively. They are defined in Eq. (3-4). The weighting factors  $x$  and  $y$  are used to control the level of impact of each criterion.  $n_{swl}$  is the number of the shifted operations.

$$c_{wi} = \frac{(c_i * P_i) - \min(c_i * P_i)}{\max(c_i * P_i) - \min(c_i * P_i)} \quad (3)$$

$$em_{wi} = \frac{(c_{em} * em_i * P_i) - \min(c_{em} * em_i * P_i)}{\max(c_{em} * em_i * P_i) - \min(c_{em} * em_i * P_i)} \quad (4)$$

where  $c_i$ ,  $em_i$  and  $P_i$  describe the price in £/MWh, the GHG emissions in tonnes of CO<sub>2</sub> eq./MWh and the active power demand in MWh for each time step  $i$  respectively. The average cost of the GHG emissions  $c_{em}$  is equal to £33/tonne of CO<sub>2</sub> equivalent [11].

There are some constraints that need to be taken into consideration. The proposed load management includes only load shifting and, thus, the daily energy should remain the same before ( $E_{old}$ ) and after ( $E_{new}$ ) the manipulation.

$$E_{new} = E_{old} \quad (5)$$

Also, in the new load curve, the peak of power demand should be lower than the old load curve. The variation of new demand during the day should be smaller in order to avoid the possibility of concentrating all the shifted load within a short period of time.

$$P_{maxnew} < P_{maxold} \quad (6)$$

where  $P_{maxnew}$  and  $P_{maxold}$  are the peak values of the active power profile.

One more limitation is that the reconnection time should not be among the two peak time slots, defined in this paper as the morning peak between 08:00 - 10:00 and the evening peak during 18:00 - 22:00 based on the typical UK residential load curve. Hence

$$i_{st} \notin [T_{peak}] \quad (7)$$

where  $i_{st}$  is the time step when the shifted load cycle is starting and  $T_{peak}$  include the periods of peak demand as defined above.

Finally, one restriction that differentiates this case from the studies on loads such as EV, is that wet loads operate in cycles which require they will start and finish without interruption. Also the operation cycles are fixed in length and magnitude.



### B. Optimisation algorithm

The price and emissions profiles are very important in the load shifting process as they define the disconnection  $t_{disc}$  and reconnection  $t_{rec}$  time step. Their direct correlation, even after the conversion of the GHG emissions profile into the equivalent cost that derives from it, is not possible because of the different scales. In order to be able to control the level of effect of each driver, both profiles are multiplied with the total power demand and then normalised. The profile that occurs is the combined cost  $c_{comb}$ , as can be seen from Eq. (1), (3) and (4).

The  $t_{disc}$  is set by the time of day when the maximum  $c_{comb}$  occurs and the wet load occurrences of this time are selected for shifting. If no wet load is present during the time of maximum  $c_{comb}$ , the nearest operation cycle is selected and used to define the  $t_{disc}$ . The time step of load reconnection  $t_{rec}$  is defined so as to achieve the targets above without violating the constraints. To fulfill this, the inverse of the  $c_{comb}$  is used to calculate the discrete cumulative probability. The  $t_{rec}$  is selected stochastically based on this probability. The result of that is to distribute the shifted loads more uniformly across the period that is considered as appropriate for reconnection and avoid the creation of a new peak.

## IV. CASE STUDY

The methodology above is applied to 7,600 households (20 LV highly urban groups of 380 households each) to represent the total loading of a typical medium voltage transformer.

Five cases are considered to study the sensitivity of the effect of the two drivers on the impact on the aggregate power demand. In the first case, only the financial criterion is taken into account, while the GHG emissions driver is ignored. The percentage of the electricity price driver reduces gradually, while the significance of the environmental criterion increases until the financial criterion reaches 0% (Table I).

TABLE I. THE SELECTED TEST CASES ON WHICH THE OPTIMISATION ALGORITHM IS APPLIED

Test case	Financial criterion contribution - $x$	Environmental criterion contribution - $y$
Case 1	1	0
Case 2	0.75	0.25
Case 3	0.50	0.50
Case 4	0.25	0.75
Case 5	0	1

### A. UK residential load

The individual demand profiles have been selected to simulate the typical UK households based on the overall

demographic characteristics of the UK population [10]. The winter weekday has been selected as the time of the simulation as it is the period that the use of wet loads is most frequent [12]. The contribution of the wet load category on the aggregate power demand of the selected group is illustrated in Fig. 1. It is obvious that the two peaks of the power demand of wet load category coincide approximately with the peaks of the total household demand.

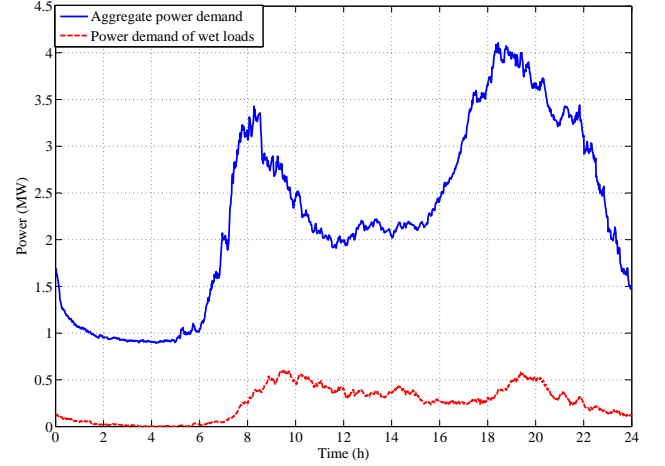


Fig. 1. Power demand of wet loads and the total household demand.

### B. Generation price and GHG emissions

Fig. 2 presents the UK daily profiles of price [7] and GHG emissions for a typical winter weekday, defined by the operating mixture of generation units at each time of day.

Although the cost of electricity for the user is a combination of a number of factors, it mostly derives from the cost of generation. For the purposes of this paper, the average electricity price is used. This depends on the contribution of all types of generation plants and remains constant due to long term contracts. Also, the electricity price is mostly formed by the power plants that work with fossil fuels, such as oil and coal, because of their high marginal cost. Any load shifting of this magnitude will create changes to the generation of these plants as they respond faster to the demand changes. For these reasons, the average values of price can be used instead of the marginal values. In Fig. 2, the price of electricity increases during most of the daytime, while the electricity is cheaper during the night highlighting the need of decongestion of the daytime load.

The GHG emissions are the marginal emissions derived from operational data of generation plants on the British grid [13]. Marginal data is required because the shift in non-critical loads will not affect the operation

of baseload plants, only those operating on the margin, which tend to have higher GHG emissions intensities. Multiple linear regression was used to determine the marginal emissions factors at different times of day for a typical winter day between November 2008 and January 2013. The method was based upon that developed by Hawkes [14] and is described in greater detail in [15]. It can be seen in Fig. 2 that the marginal GHG emissions fluctuate throughout the day, but tend to be higher at times of low demand. This is likely to be due to coal-fired plants being the marginal generators at these times, while gas-fired power stations (which have lower GHG emissions) are the marginal generator at times of high demand. This relationship is mostly determined by the relative prices of coal and gas, suggesting that coal has generally been cheaper than gas.

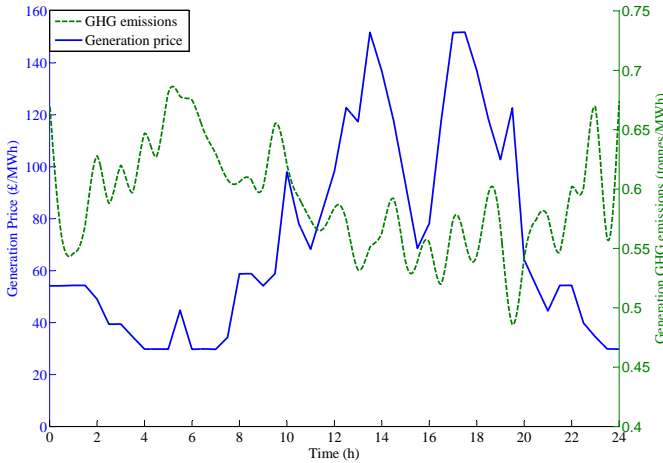


Fig. 2. Daily profiles of price and GHG emissions per MWh [7], [15].

Fig. 3 depicts the normalised cost that combines the price of electricity and the equivalent cost of the GHG emissions for each case according to Eq. (1), (3) and (4). It can be seen that the profile of price dominates and affects the combined cost despite the normalisation and its low contribution.

### C. Results

The results of the optimisation algorithm on the selected cases are presented here. In Fig. 4(a), the change in combined cost for each shifted operation cycle of the wet loads is presented while the black dots indicate the number of required cycle shiftings to achieve the minimum combined cost. Fig. 4(b) shows that in all cases, even when the contribution of electricity price is either small or zero, there is some reduction in cost and the minimum total cost is reached after approximately 5140-5300 shiftings depending on the case. Also, it is

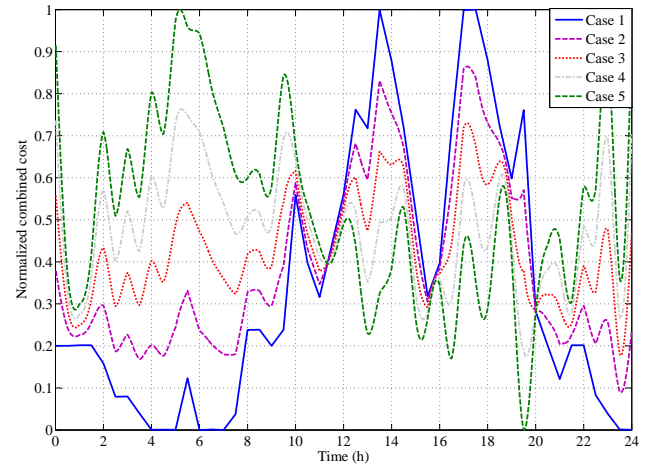


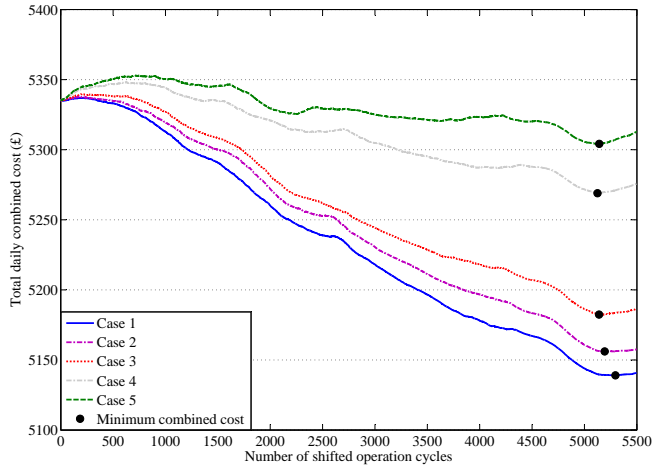
Fig. 3. Normalised combined cost profile for each case according to Eq. (1), (3) and (4).

clearly seen that the price has greater influence on the combined cost than GHG emissions despite the equal weighting (case 3) as observed in Fig. 3

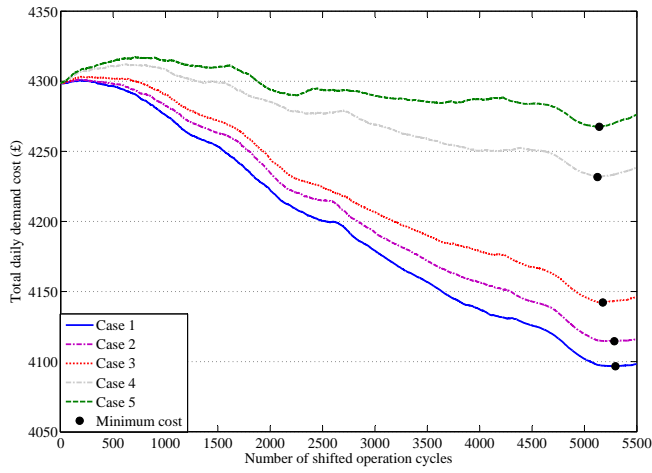
The effect on the marginal GHG emissions, as it is presented in Fig. 4(c), is interesting. The GHG emissions in cases 2 and 3 remain almost constant for approximately 1500 shiftings and then actually increase, while, on the other hand, it can be seen that it is possible to reduce the emissions in cases 4 and 5 for the first 3500 shiftings. The maximum savings occur at 2000 shiftings in case 4 and 1500 shiftings in case 5.

Further details are presented in Fig. 5(a), which shows how the power demand of the load category of the wet appliances reshapes after the management technique is applied in all cases. Intuitively, in the cases where the weighting favours cost over GHG emissions, it is observed that the operation of the wet loads is limited during the daytime when the electricity is more expensive and the majority of the wet load has been shifted towards the night-time. However, the increased consumption during early in the morning is the reason behind the increase of the amount of emissions in these cases (Fig. 4(c)). In cases 4 and 5, the increased influence of GHG emissions on the combined cost is perceptible on the new power demand curves. Also, it is clear that the increased demand after midnight (00:00-04:00) reduces the electricity price enough to cover the cost of the demand during daytime when electricity is more expensive, this explains the fact that the total cost reduces in case 5 (Fig. 4(c)). The result of avoiding the reconnection of loads during peak hours is also visible.

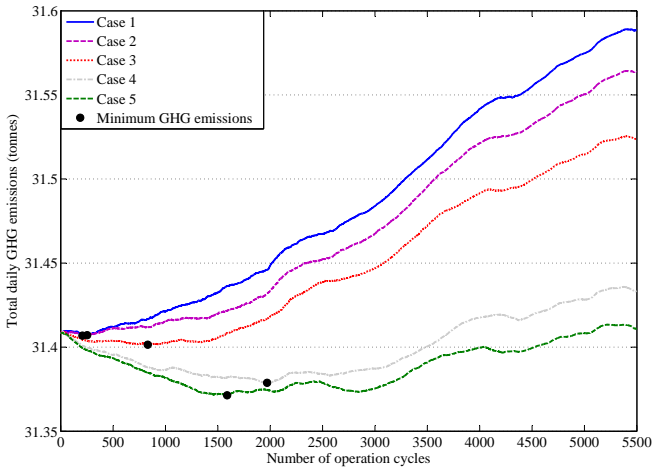
Fig. 6 also shows that the maximum reduction on the combined cost reached about 3.7%. However, the individual savings on total daily cost and the GHG



(a) Total combined cost



(b) Total price



(c) Total GHG emissions

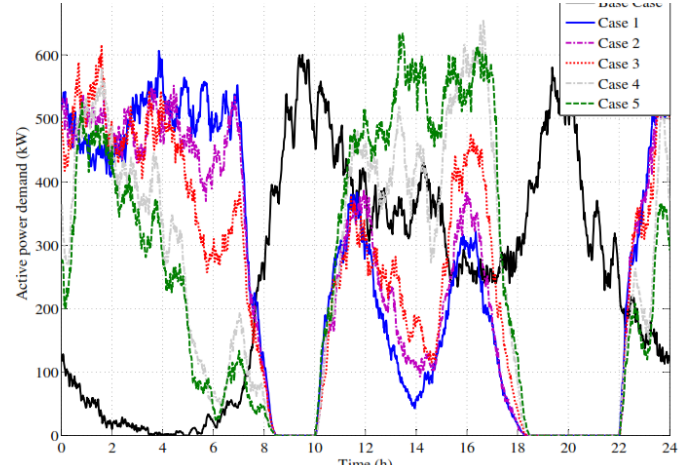
Fig. 4. Differentiation of total combined cost, price and GHG emissions according to the number of load shiftings for each case.

emissions reached about 4.7% and 1%, respectively. This shows the attempt of the code to balance the two drivers, despite the greater influence of price. Further details on the savings for each case are presented in Table II.

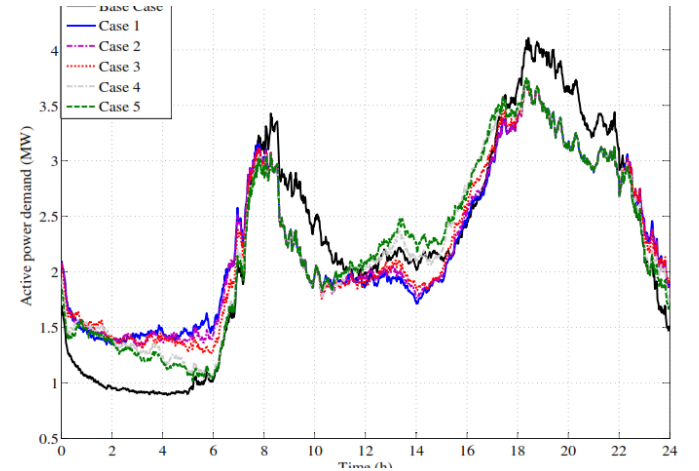
TABLE II. SAVINGS AMONG TEST CASES

Test Case	Total combined cost savings	Total cost savings	Total GHG emissions savings
Case 1	3.7%	4.7%	
Case 2	3.4%	4.4%	<0.01%
Case 3	2.9%	3.6%	
Case 4	1.2%	1.5%	0.8%
Case 5	0.6%	1.0%	1.0%

The effect of the reformed power curve of the wet loads on the aggregated power curve is demonstrated in Fig. 5(b). The power during the peak hours has reduced from 8.5% to 8.9% in the evening and 7.8% to 10.9% in the morning which will help to alleviate stress in the electrical network. The power during night time has increased significantly by 5 to 50%, according to the case and time. The power demand decreases during midday for cases 1-3 and increases for cases 4 and 5, showing the influence of the weighting between the financial and environmental criteria.



(a) Active power demand of wet loads



(b) Daily active power profile

Fig. 5. Active power demand of the wet loads and total residential demand before and after load shifting for minimum daily cost.



As mentioned previously, the maximum savings of GHG emissions occur after a low number of shiftings, from 250 to 1970 depending on the test cases. Fig. 6(a) and 6(b) present the change in the power demand of wet load and the aggregate load after those shiftings. Although the number of shifted operations is small, it is enough to observe the operation of the algorithm: up to this point, the operation cycles are moved to achieve both targets (cases 2-4). Loads are disconnected from the evening peak and reconnected at night. In this way, both the emissions and the cost reduce, resulting in the relief of the evening peak.

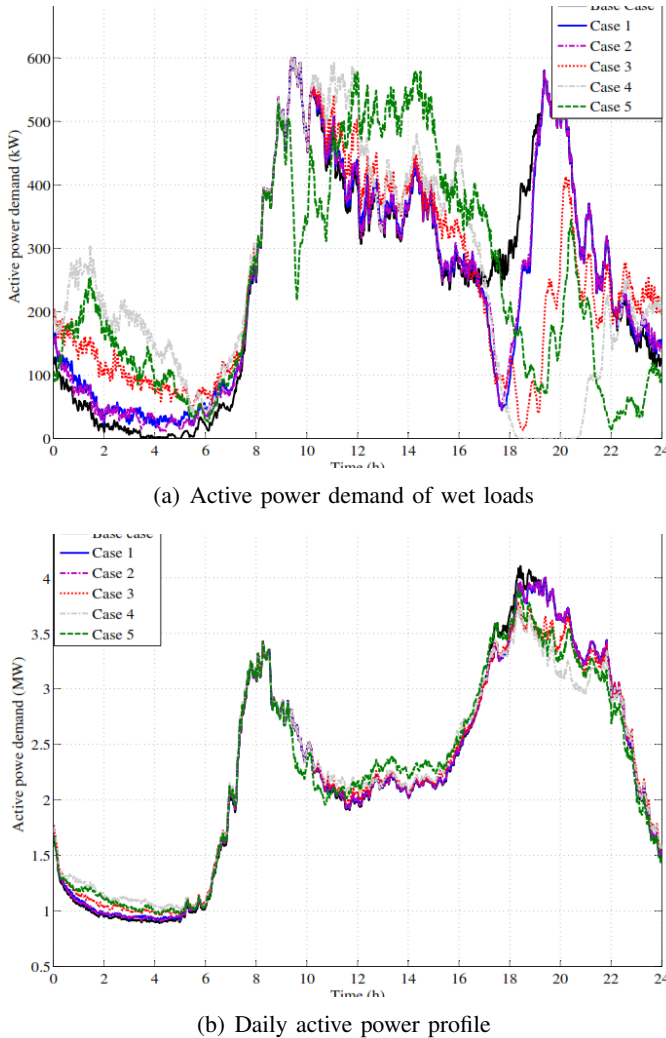


Fig. 6. Active power demand of the wet loads and total residential demand before and after load shifting for minimum GHG emissions.

## V. CONCLUSION

This paper has shown that management of LV loads allow for significant reductions in cost and GHG emissions. This study combines the average values of electricity price and marginal GHG emissions with detailed models of LV residential loads, through a multi-objective optimisation algorithm. The results show that

the financial factor has a greater impact in shaping the combined total cost, implying that it is more difficult to achieve GHG emissions savings than cost reductions by residential load shiftings. This may explain the current situation of generation, where price is the main objective and GHG emissions become difficult to decrease.

The volume of reductions suggest that DSM actions on non-critical loads applied on LV level and at a larger scale can lead to reductions in price and GHG emissions comparable to those achieved by distributed generation (DG). In the future, larger group of households could be used to investigate this possibility. Also, a network analysis could be performed to study the reaction of the network characteristics to these DSM actions and any further potential benefits.

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# Voltage Control of UK Residential Customers for Power Reduction

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**Abstract**—Reducing peak system demand is generally regarded as a crucial step in deferring investment in electricity networks and improving overall performance. Several utilities have explored the use of voltage control for peak reduction but the results are inconclusive. This paper presents results of an ongoing study of the potential of voltage control for demand reduction within the UK distribution network. A stochastic simulation approach using detailed low-voltage residential load models and network models is implemented to quantify the scale of demand reduction for step change in voltage magnitude.

**Index Terms**-- distribution network, load modelling, residential load, smart grid, voltage control.

## I. INTRODUCTION

Maintaining supply voltage within the required limits is one of the key requirements of the electrical power system. To achieve this, various devices (e.g. static VAR units or OLTC transformers) are installed throughout the system to maintain the voltage magnitude within operational limits. Previous research has shown that it is possible to reduce the active power demand of the load by using these voltage control devices to lower the voltage magnitude during hours of high demand [1-5]. Although, it is often said that a “1% voltage drop will result in a 1% decrease in power demand” [5], the power reduction cannot be easily quantified. This is confirmed by previous research, from which two general conclusions can be drawn [1-5]:

- The typical active power reduction is between 0.4-1% per 1% voltage reduction
- The results are hard to predict and are influenced by the location, time of day and time of year

The power demand response of the network load to a step change in voltage magnitude is a combination of the electrical characteristics of the load, which are a function of the supply voltage, and the performance of the network. As the load composition will change between geographic locations and will also exhibit short term (e.g. daily) and long term (e.g.

seasonal) variations, the electrical characteristics of the load are highly variable. Accordingly, the potential benefits of a voltage control scheme will also exhibit temporal and spatial variations and requires detailed knowledge of the connected load.

Previous research in this area is based solely on field tests and measurements at distribution system substations [1, 2, 5] or in individual commercial and residential buildings [3, 4]. To obtain a representative set of results, a large number of staged tests would be required to determine the possible range of power reduction. This requires financial investment, if monitoring equipment is not already installed at the required location, and time to fully include seasonal and daily variations. However, computer simulation techniques allow for the analysis of a larger number of scenarios and system operating conditions.

This paper utilises a stochastic simulation approach to present initial results of a detailed analysis of the contribution of voltage control for demand reduction within the UK distribution networks. The simulation approach includes the use of detailed low-voltage (LV) models of the UK residential load and network to quantify the changes in demand reduction for different network/load configurations during the day for 1% and 3% supply voltage reductions. In addition to the recorded active/reactive power reduction, the paper will also consider the impact on the efficiency, i.e. losses, and the voltage profiles within the LV network.

The analysis presented in this paper will focus on the LV network supplying only residential load. The simulation period is taken as winter weekend, as this represents the peak loading conditions of the UK residential load sector. Although the secondary distribution transformer (11/0.4 kV) does not include voltage control functionality (beyond manual tap changes for seasonal demand variations), it is assumed that the voltage on the primary winding can be controlled by manually adjusting the system impedance of the infeder, to represent staged voltage drop actions. Future analysis will focus on larger area networks with a mix of loading conditions and

include the load voltage control functionality of the 33/11kV OLTC transformers.

The paper is structured as follows, in the first Section an overview of the proposed modelling approach is presented, followed by the simulation framework in Section II. Section III introduces the LV load models used in the paper. In Section IV, the network characteristics and the use of load characteristics are described, while the results for each case are presented in Section V. Conclusions and suggestions for further work are given in Section VI.

## II. SIMULATION FRAMEWORK

The simulation framework applied to analyse network/load response to voltage reduction in this paper consists of the following steps:

- Define network/load configuration and time of year. Build detailed LV models of the UK residential loads, using the load modelling tool developed in previous research, see [6, 7] for further details.
- Build detailed LV network models and connect residential load models.
- Simulate steady state conditions for base case comparison.
- Simulate network with voltage reduction at 1%/3%.
- Analyse simulation results and quantify changes in active and reactive power and losses.

## III. LOW-VOLTAGE LOAD CHARACTERISTICS

The electrical characteristics of power system loads will change as a function of the supply conditions, i.e. voltage magnitude and frequency. Traditionally, loads were defined as one of three types: constant impedance, constant current or constant power. These three load types are shown in Fig. 1. The corresponding changes in load current magnitude (assuming a dc power flow) are also shown.

The results in Fig. 1 clearly illustrate why the type of load connected will influence the power demand savings for voltage reduction. For example, although the power demand of a constant power load will not change by reducing the voltage, the current will increase, which will result in higher losses across the network impedance.

In this paper, the loads are represented with static load models. Static load models define the load characteristics as a function of only the current supply conditions and are generally used for steady-state power flow calculations. Two of the most widely used static load models are:

- Exponential model

$$P = P_0 \left( \frac{V}{V_0} \right)^{n_p} \quad (1)$$

- Polynomial model (commonly referred to as ZIP)

$$P = P_0 \left[ Z_p \left( \frac{V}{V_0} \right)^2 + I_p \left( \frac{V}{V_0} \right) + P_p \right] \quad (2)$$

where:  $P$  and  $V$  are the actual active power demand and supply system voltage accordingly,  $P_0$  and  $V_0$  are the nominal/rated corresponding values,  $n_p$  is the exponential model coefficient and  $Z_p$ ,  $I_p$ ,  $P_p$  are the polynomial/ZIP model coefficients. Reactive power is represented by equivalent expressions.

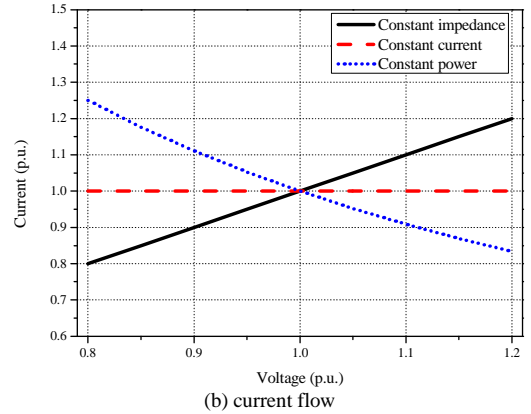
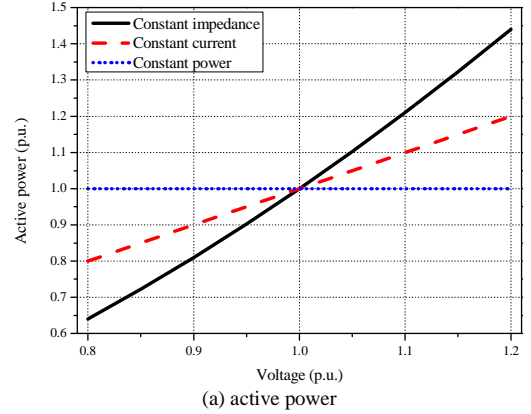


Figure 1. Traditional load characteristics.

Although the polynomial load model is used during simulations, the exponential load model coefficients are used in this paper to present results, as it allows for a clearer display of the characteristics with only one coefficient.

### A. UK residential load

The detailed household load profiles and load models used in this paper are based on the user activity profile of each occupant, which is developed using the Markov-chain Monte Carlo simulation technique. The user activity profiles are aggregated into a household activity profile (if more than one user in the household) and are combined with the available device statistics (ownership, electrical characteristics and use statistics) and a database of ambient conditions to develop the power demand profile of household. The power demand

profile is converted into electrical load models by aggregating the load model of each device that operates at the same time interval. More details on all aspects of load models development can be found in [6, 7].

Table I presents the load models of the most commonly used load types in the UK residential load sector used in the model development process. Lighting is modelled as incandescent (GIL) or compact fluorescent (CFL). Motor load types are used to represent cold appliances (refrigerators and freezers) and water pumps. Loads that are used for heating, such as space and water heating, electric hobs/ovens and kettles, are assumed to be ideal resistive loads. Consumer electronic devices and ICT are modelled as “switch-mode power supply” (SMPS). Depending on rated power, electronic devices can be equipped without power factor correction (no-PFC), with passive PFC (p-PFC) or active PFC (a-PFC). These are discussed in more detail in [8]. Appliances with operating cycles (e.g. dishwashers, washing machines and tumble dryers) are modelled according to the function that is being done at each time step.

TABLE I. EXPONENTIAL/POLYNOMIAL LOAD MODEL COEFFICIENTS [8]

Load	PF <sub>1</sub>	Exp.		Polynomial					
		$n_p$	$n_r$	$Z_p$	$I_p$	$P_p$	$Z_o$	$I_o$	$P_o$
GIL	1	1.55	-	0.43	0.69	-0.12	-	-	-
CFL	0.91	0.98	0.93	-0.01	0.96	0.05	0.1	-0.73	-0.37
RSIR <sub>CT</sub>	0.62	0.06	1.92	0.63	-1.2	1.57	-1.4	-0.91	-0.5
RSIR <sub>QT</sub>	0.62	0.30	1.92	0.10	0.10	0.80	1.40	-0.91	0.50
RSCR <sub>CT</sub>	0.90	0.38	1.68	0.50	-0.62	1.11	1.54	-1.43	0.89
Resistive	1	2	-	1	0	0	-	-	-
SMPS <sub>noPFC</sub>	0.994	0	2.36	0	0	1	-3.63	9.88	-7.25
SMPS <sub>pPFC</sub>	0.97	0	-0.5	0	0	1	0.45	-1.44	1.99
SMPS <sub>aPFC</sub>	1	0	-	0	0	1	0	0	0

Where: GIL is general incandescent light, CFL is compact/linear fluorescent lamps, RSIR<sub>CT/QT</sub> stands for Resistive Start – Induction Run motors with constant/quadratic torque, RSCR are Resistive Start – Capacitor Run motors and SMPS (no-PFC/p-PFC/a-PFC) stands for “switch-mode power supply” (digital) devices with no/passive/active power factor correction

#### IV. IMPLEMENTATION

This section illustrates how the methodology outlined in Section II is implemented using generic models of two typical UK LV network configurations (highly-urban with 380 customers and sub-urban with 76 customers), which represent the cases of heavily and lightly loaded LV networks [9].

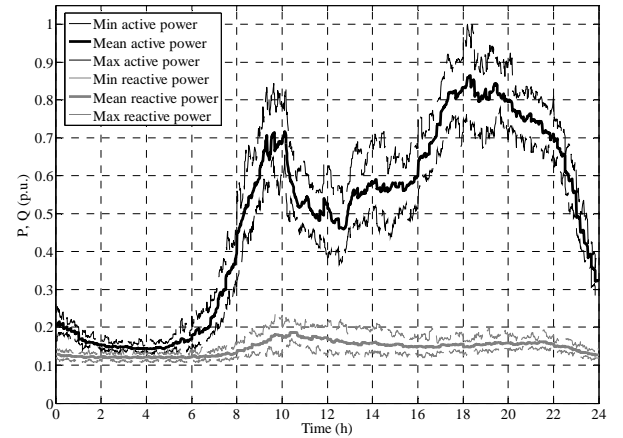
##### A. User Profiles

The two selected networks were populated using the load models introduced in previous section. The composition of customers is based on the UK-wide demographic characteristics given in [10, 11] and are presented in Table II. Although the demographic characteristics are likely to vary across the network, for this paper it is assumed that they are identical to allow for a fair comparison of results.

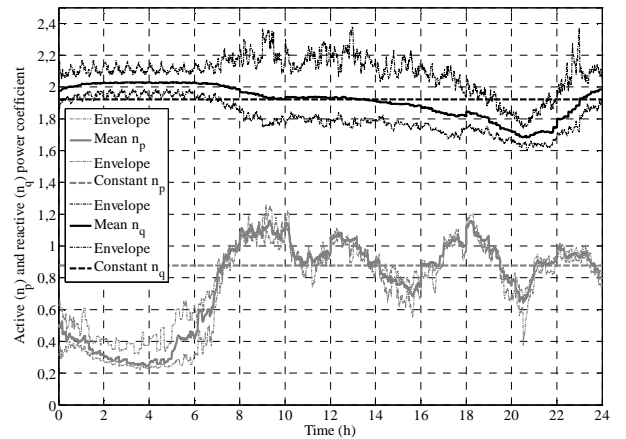
Using the stochastic profiles, simulations were repeated until the results achieve an asymptote value. In Fig. 2a, the mean, minimum and maximum value of a large number of simulations for active and reactive power demands of the highly urban network are shown. It can be seen that the mean

active power, the thick black line, has two main peaks, one in the morning (08:00-10:00) and another in evening (17:00-22:00). The light black lines show the minimum and maximum active power demand at each time step and represent the variation within the simulation load profiles. In the sub-urban network, the input data have the same characteristics but exhibit increased variation due to the smaller sample size.

The aggregate active and reactive power coefficient of exponential load model is presented in Fig. 2b. From the mean  $n_p$  of all customers, thick grey line, it can be seen that during the night and early in the morning the load is approximately constant power load because of the small value of  $n_p$ . However, during the day, it behaves more as a constant current load. The narrow envelope, light grey line, indicates a small variation in the aggregate active power characteristics. Although the reactive power characteristics have an increased range, there is less variation between simulated groups of customers across the 24hr period and it is very close to constant impedance load type.



(a) scaled active and reactive power demand



(b) aggregate active and reactive power coefficient of exponential load model

Figure 2. Variation in active and reactive power demand and active and reactive power coefficient of exponential load model for UK residential customers, for January weekend.

TABLE II. ASSUMED DEMOGRAPHIC CHARACTERISTICS FOR SCOTLAND, BASED ON DATA IN [10, 11]

Household size	Number of working occupants	Percentage
1	0	11.6
	1	23.2
2	0	3
	1	8.4
	2	23.3
3	0	1.3
	1	3.8
	2	10.4
	3	1.3
4	0	1
	1	2.9
	2	8.2
	3	1.1
	4	0.5

Also shown in Fig. 2b is the daily weighted mean of the load model coefficients. The weighted mean is calculated from the product of coefficient, e.g.  $Z_p$ , and rated power  $P_0$  at time  $t$  for household  $k$ , over the total power demand at the same time step (3). The resulting weighted mean value confirms the general aggregate characteristics of the LV load: close to constant current for active power, with reactive power approximating a constant impedance load type. The weighted mean values are displayed in Table III.

$$\begin{bmatrix} Z_{p,q\_mean} \\ I_{p,q\_mean} \\ P_{p,q\_mean} \end{bmatrix} = \begin{bmatrix} Z_{p,q}^{kt} \\ I_{p,q}^{kt} \\ P_{p,q}^{kt} \end{bmatrix} \frac{\begin{bmatrix} P_0^{kt} \\ Q_0^{kt} \end{bmatrix}}{\sum_{i=1}^N \begin{bmatrix} P_0^{it} \\ Q_0^{it} \end{bmatrix}}, \quad t \in [1, T] \quad (3)$$

where:  $P_0$  and  $Q_0$  is the nominal/rated of active power,  $Z_p$ ,  $I_p$ ,  $P_p$  and  $Z_q$ ,  $I_q$ ,  $P_q$  are the polynomial/ZIP model coefficients of active and reactive power,  $T$  is the total number of time steps and  $N$  is the number of customers/customers group.

TABLE III. WEIGHTED MEAN OF POWER MODEL COEFFICIENTS FOR THE STEADY STATE COMPARISON

Exponential		Polynomial					
$n_p$	$n_q$	$Z_p$	$I_p$	$P_p$	$Z_q$	$I_q$	$P_q$
0.8766	1.9219	0.4001	0.0763	0.5235	1.0419	-0.5804	0.3208

## B. Network

In this paper, only the LV network is considered. Although they are part of larger network in reality, the models used here are isolated LV systems. The voltage control is simulated by changing the system impedance of the infeeders to obtain the required voltage drop at the primary winding.

The highly-urban sector represents households in cities and are usually connected on an underground, radial network supplied by an 11/0.4 kV transformer. The network is characterised by high load density and short cable lengths.

Four branches are connected to a 1 MVA transformer supplying a total of 380 single-phase customers. In suburban areas of cities, in regions close to cities or small towns, the network is overhead and connected on an 11/0.4 kV transformer of lower rating than the one in highly-urban LV sub-sector (0.2 MVA). The typical sub-urban network consists of two branches of overhead line and 76 single-phase customers connected by underground line.

The line characteristics of the networks above can be seen in Table IV. More details on the network design and configuration can be found in [13, 14].

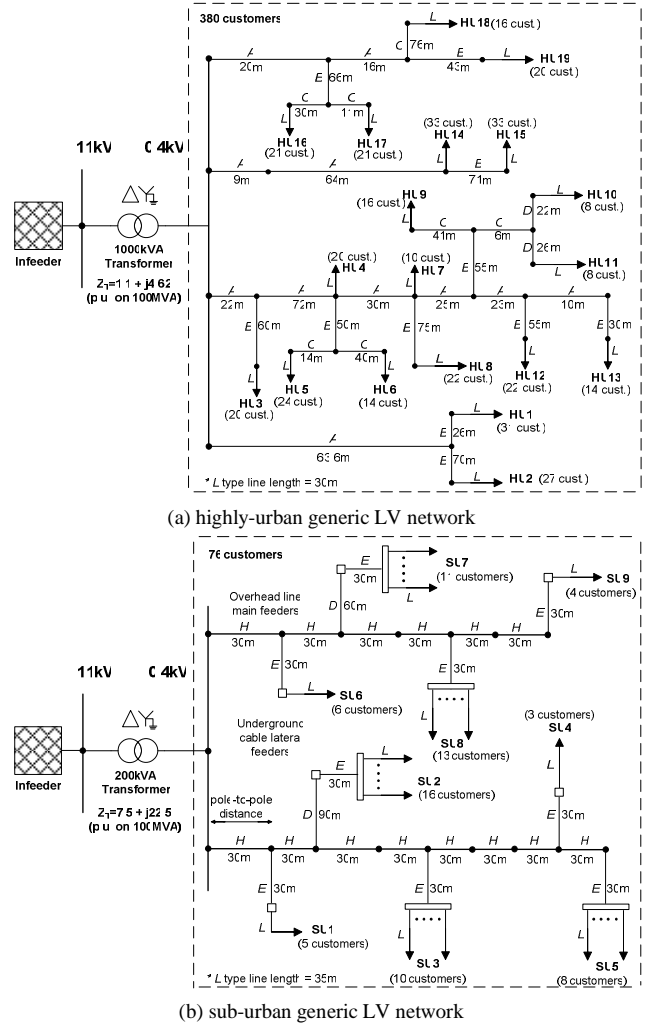


Figure 3. Single line equivalent generic LV distribution networks, based on data in [13, 14].

## V. RESULTS

### A. Active/Reactive power

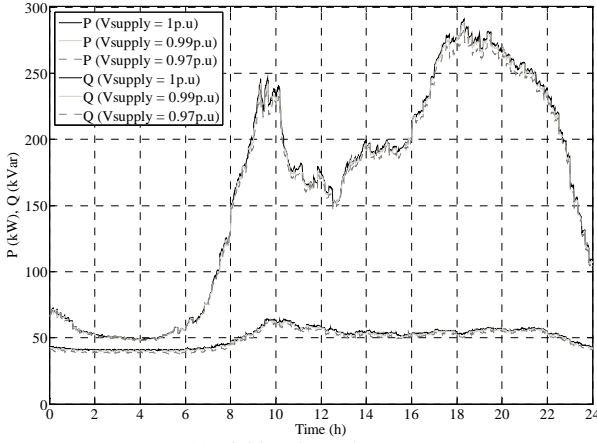
Fig. 4 presents the mean active and reactive power demand of customers for each network for 1% and 3% voltage reduction. The results are more clearly displayed in Fig. 5,



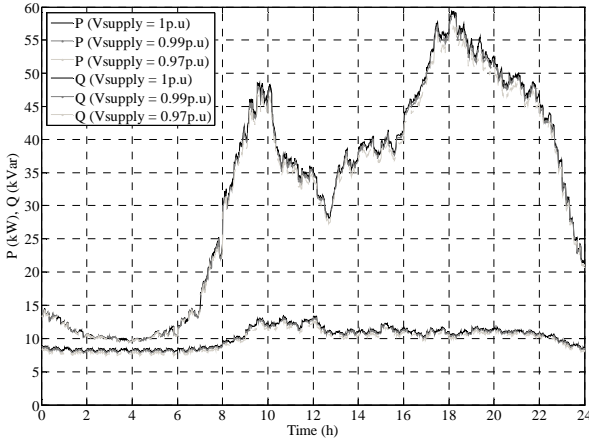
TABLE IV. CONFIGURATION AND PARAMETERS OF THE LV LINES IN THE USED SUB-SECTORS [13]

Line Id.	Cross sectional Area (CSA)	Positive sequence	
		$R_{ph}$	$X_{ph}$
	$(mm^2)$	$(\Omega/km)$	
Underground Line (Cable)			
A	300	0.1	0.073
B	185	0.164	0.074
C	120	0.253	0.071
D	95	0.320	0.075
E	70	0.443	0.076
Overhead Line			
H	95	0.32	0.085
Service Connection			
L	35	0.851	0.041

which shows the variation of the percentage of active and reactive power variation during the day. It can be seen that the power reduction percentage is following the  $n_p$  and  $n_q$  curves.



(a) Highly-urban sub-sector



(b) Sub-urban sub-sector

Figure 4. Active and reactive power reduction in the two test networks due to voltage reduction.

In Fig. 4 and 5, it is observed that the greater power saving occurs during the peak hours. Also it is seen that at the same time intervals, the percentage reduction of reactive power is

larger than the equivalent of active power. This will have an impact on the power factor of the whole system.

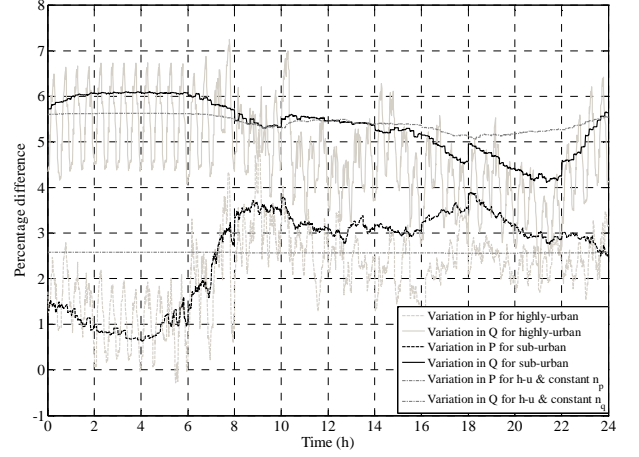


Figure 5. Percentage variation in active and reactive power during the day for 3% voltage reduction for both networks.

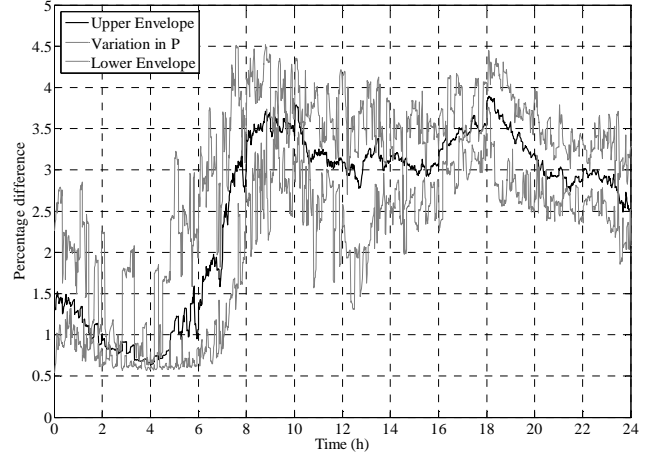


Figure 6. The envelope of percentage variation of active power percentage reduction in sub-urban network for 3% voltage reduction.

The results in Fig. 6 show a more detailed analysis of active power reduction and displays the range of values obtained. These results show a margin of 2.5-4.5% during peak loading times, with a much more modest reduction of 0.5- 2.0% during night-time. When using the constant values of weighted mean value polynomial model, the percentage reduction of power demand remains approximately constant during the day. Therefore, this will over-estimate the reduction during the night-time and underestimate the reduction during the peak hours, which are of most significance.

## B. Voltage

One factor that has to be considered is the limits on voltage variation. In UK, the nominal voltage of the LV network is 230/400V with a tolerance margin of +10/-6%. If voltage control applies, this restriction can be an issue during the time of peak demand, when the voltage magnitude is

reduced from the nominal value. Lowering the voltage magnitude further may lead to voltage violations.

Fig. 7 presents the voltage variation on the node with the most distant load for the two tested networks (highly-urban HU9 and sub-urban SU5 in Fig. 3). The thick lines show the mean voltage magnitude and the light lines represent the minimum and maximum values. The minimum voltage is recorded at this node and it can be seen that, when the voltage supply is reduced by 3%, the voltage is dropped relatively close to the lower limits of the supplied voltage. This is more likely to present a problem when the isolated LV networks are connected to distribution networks, as the inherent voltage drops within this system will reduce the voltage magnitude at the primary of the LV secondary distribution transformer.

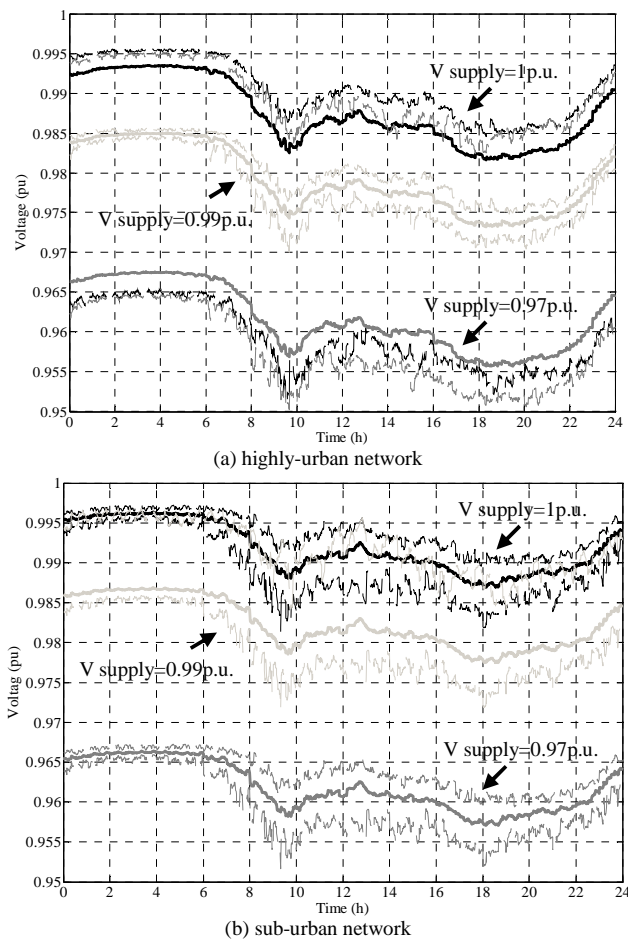


Figure 7. Voltage variation on the most distant load during the day for both networks.

### C. Losses

The losses recorded in the LV networks are not significantly affected by the different scenarios. There is approximately a 0.33% difference per 1% voltage reduction. This negligible difference can be attributed to the aggregate load characteristics. From the aggregated  $n_p$  of total load

model (Fig. 2b) which is close to 1, it is noticed that the load behaves more like a constant current load and thus the transmission losses remain approximately constant.

## VI. CONCLUSIONS AND FURTHER WORK

This paper has presented some preliminary results the potential of voltage control of LV networks to reduce power demand. The stochastic simulation approach taken in this paper differs from the previous research in this area, which is based on field measurements, but the general conclusions are similar. However, the additional detail available using the approach presented in this paper helps to illustrate the potential variation in active power reduction.

Furthermore, the performance of the detailed time-varying load models was demonstrated by comparing against a weighted mean load model, which was shown to underestimate the demand reduction during peak hours. Future research will focus on applying this analysis to a wider network supplied from 33/11 kV OLTC transformer with more customers, where the expected influence will be greater.

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